MENGM0056
Product and Production Systems Coursework

Group 109 - Dominic Kemp, Jonny Macha, Felix Newport–Mangell, Mark Woodward

Executive Summary

This project investigates and improves the production system of a hand-cranked pasta maker. *Acme Kitchenware* is an established company looking to offer a competitive product to the mid-range pasta maker market and it is estimated that *Acme* could supply an annual demand of 30,000 units by capitalising on seasonal demand fluctuations in the US.

Key performance indicators (KPIs) were researched and assessed in the context of *Acme's* goals. Following a down-selection process, the KPIs of lead time, system utilisation (SU), and work in process were found to be critical to the success of the factory producing *Acme*'s pasta makers. Four optimisation objectives were selected to improve at least one KPI in each case: system scheduling with linear programming, machining detailed scheduling with a genetic algorithm, product re-design for improved assembly, and including quality-at-source (QAS) to minimise waste in product reprocessing.

Tasks yielded significant KPI improvements over baselines. System scheduling improved system utilisation by 103%, from 0.35 baseline average to 0.72 – a side-effect was a reduction in annual average work in process, from 200,000 to 70,000 parts in the system. Machining scheduling enabled tasks to be completed within the working month and increased system utilisation from 0.42 to 0.66 using an additional lathe. Changes to batch size, a product redesign and new worker training in the assembly cell provided improvements to lead time up to 25%, 40% and 35% respectively and cause up to a 20% reduction in WIP. Quality-at-source (QAS) reduces the rate of increase of WIP in the assembly system matching performance achieved when an extra worker is hired. Error-proofing hindered rising WIP over 1 month and demonstrated a 7.6% increase in SU at high demand when the error rate is halved.

Recommendations have been made to *Acme,* with an assessment of the potential gains to be derived from each, and an estimate of the up-front capital expenditure and factory downtime needed to implement changes.

1 Introduction

1.1 Product

This report considers the design and improvement of a mid-range hand-crank pasta maker and the factory producing them. The product rolls pasta into thin sheets before it is sliced and cooked separately. This is a leisure and kitchenware product that is part of the growth of high-quality and adventurous home cooking. The product design is based on the core rolling element of the 'Imperia' pasta maker and excludes its additional attachments. Acme Kitchenware (*Acme*) has integrated the product into the US consumer goods and kitchenware market. *Acme* is a manufacturer and seller of a range of kitchen and household products, with a both strong brand and existing sales infrastructure in the U.S.

The pasta maker design and a partially exploded view were modelled in Autodesk Fusion and are shown in Figure 1. The product comprises two rollers with an adjustable gap to output the desired thickness of pasta. These rollers are actuated by a hand crank and supported by a sheet metal structure which protects the internal mechanisms.

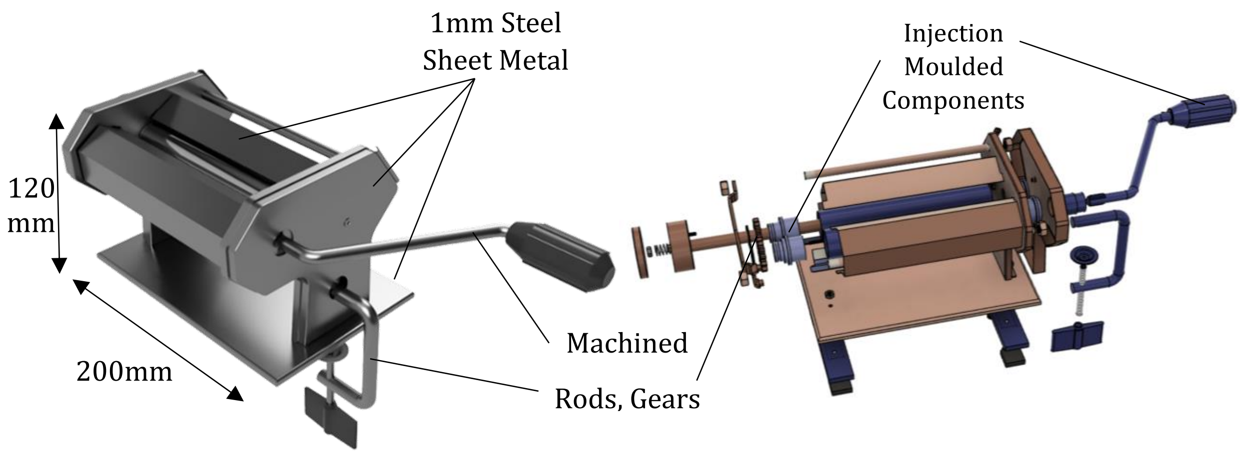


Figure 1 : Pasta Maker, Design and Exploded view.

Table 1: Product assembly breakdown.

Component Type	Source Material	Total Number	Unique Parts
Machined Parts	Steel Bar	10	8
Sheet Metal Parts	Steel Sheet	14	12
Injection-Moulded	Nylon and PVC grains	12	5
Standard	n/a	20	6
Total	-	56	31

Table 2: Product Component Breakdown.

Assembly Type	Stages
Sub-Assemblies	5
Main-Assembly	7
Total	12

Of the 31 unique parts, approximately one-third of the components are cut and press-formed from stainless steel sheet metal. The 10 machined parts require multistage processes including milling, lathing and rod-bending. Table 1 identifies the source material for product elements and the number of unique elements. The assembly of the product is a multi-stage process completed by hand (Table 2).

1.2 Production

The base case for this analysis considers an existing production system that requires improvement. The warehouse space is rented and fitted for the manufacture of the hand-crank pasta maker and process machines have been bought outright prior to production. The Atlas of Economic Complexity statistical database reveals the U.S. is a large global importer of pasta-making machinery with a 9.85% share and a 5.7% global share of exports in 2020 [1]. Improving the current factory in the U.S. will complement the *Acme* company's existing sales infrastructure across North America.

The hand-crank pasta maker production system currently achieves an output based on previous annual demand. The core components of the production system process have been summarised as a flow chart in Figure 2. For completeness Table A1 in Appendix A summarises all the parts involved in the process.

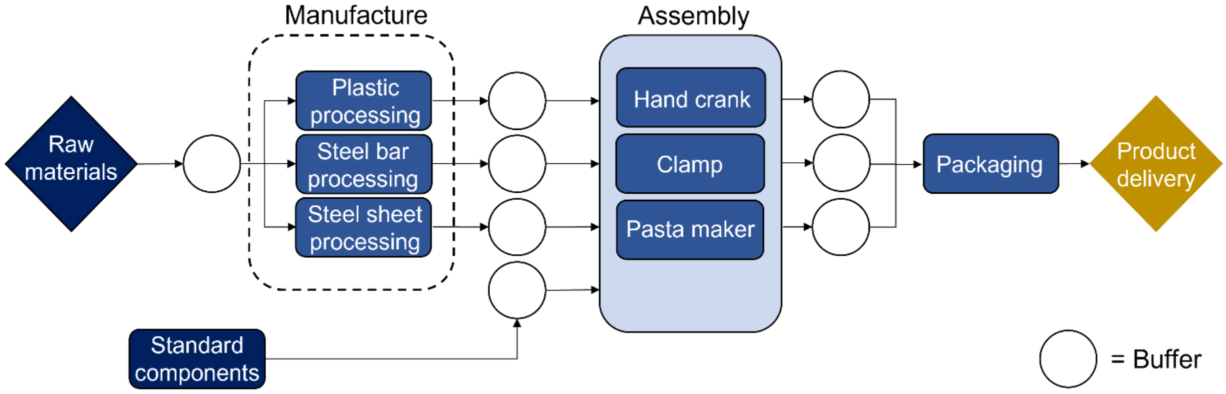


Figure 2: Production system flowchart.

1.3 Demand Modelling

The *Acme* Pasta Maker's targeted end users are purchasers of domestic and household kitchenware. This product category entails a high sales volume to the mass market, in which exists considerable competition of very similar products at competitive prices.

Two approaches were taken to estimate the share of the market that *Acme* could achieve. The equations and estimates used are detailed in Appendix B and concluded a demand of 2500 sales/month.

To gain a better understanding of how production would need to adapt throughout the year in response to seasonal demand, an annual sales forecast estimate was established. This was carried out using kitchenware quarterly sales data [2] and adjusted with consideration for *Acme's* strategy of leveraging increased exposure to consumers with discount prices during *Amazon Prime Day*s [3] in July and October – with the expectation that demand surges would be seen in those months.

1.4 Conversion to Lean Manufacturing

Acme is aiming to improve the current hand-crank pasta maker production system by implementing changes that align with the lean manufacturing philosophy:

'*Lean production is aimed at the elimination of waste in every area of production…Its goal is to incorporate less human effort, less inventory, less time to develop products, and less space to become highly responsive to customer demand while producing top quality products in the most efficient and economical manner possible.'* [4]

Multiple case studies have demonstrated that implementing lean manufacturing in high-volume production systems can increase performance in quality, flexibility, delivery, and cost [5], [6]. Demand for the *Acme* hand-crank pasta maker is expected to rise in the future, and the production system must be adaptable to sharp increases in demand such as seasonal fluctuations from a consumer 'pull'. Furthermore, a consistent level of quality will be expected from *Acme*'s strong, and growing customer base. Moreover, *Acme* aims to eliminate or minimise waste in high-risk areas of the current production system. Waste is defined as any process in a system that does not add value to the customer. Within the lean perspective, eight sources of waste exist: waiting, overproduction, over-specification, transportation, inventory, rework/scrap, motion (inefficient processes), and employee potential [7].

2 KPI Selection

The identified performance objectives for this production system include quality, adaptability (or flexibility), and delivery. Research has shown that cost benefits can be satisfied with high quality, timely delivery, and flexible production [5], [8].

KPIs quantify the performance of the system based on the above objectives and help to focus the improvements. This scheme of work will investigate 3 KPIs for system optimisation and improvement. KPIs were considered from literature and reviewed before down-selection via Pugh Matrix [9].

The results from this analysis concluded the 3 KPIs as lead time, system utilisation and work in process (WIP). The analysis tables can be found in Appendix C. Discussion of how these KPIs meet *Acme*'s objectives is outlined below.

2.1 Lead Time (T)

This report defines lead time as the time between the customer ordering and receiving their product [9], see Equation 1.1. By decreasing lead time, *Acme* increases flexibility to likely demand spikes such as might be observed on Amazon Prime Days or in seasonal periods. Due to the competitive market, it is vital in busy seasons business is not lost due to increased lead time. Reducing lead time for the same demand could result in a reduced factory operating period, cutting labour, and building costs. In this event, *Acme* might even consider relocation to a smaller factory or operating for less than 12 months of the year. This would provide an opportunity for the current factory to be utilised by another *Acme* product further growing the business.

$$T = absolute\ order\ time - absolute\ delivery\ time \quad (1.1)$$

2.2 System utilisation (SU)

System utilisation is defined as the mean proportion of time which stations are adding value compared to their total time in operation [9], see Equation 1.2. Improvements to SU will improve the idle time of parts within the system, contributing to a leaner system and a particular reduction in waste in both human resource and waiting. This is relevant given the competitive market in which *Acme*'s Pasta Maker exists, with a growing customer base. Utilisation improvements that can be gained on competitors may increase the long-term viability of this line of products. A quality improvement can be measured as an increased proportion of value-adding activities. Maintaining the mid-range product quality of *Acme,* or improving it, is important for *Acme* and will make the product more competitive at market.

$$SU = \frac{\sum_{i=1}^{n} \frac{time\ adding\ value\ at\ station\ i}{time\ at\ station\ i}}{n} \quad (1.2)$$

2.3 Work in Process (WIP)

WIP is defined as part count between stock and product [10]. Reducing inventory and storage within the system is a core element of the transition to a lean system. The reduction of components or assemblies idling in queues can reduce bottlenecks and increase flexibility in response to demand spikes or changes in production rate. By improving WIP *Acme* can also reduce the initial investment required for materials and parts, making products closer to order and freeing capital for other areas of the business.

$$Work\ in\ Process = WIP = no.of\ parts\ and\ subassemblies\ in\ entire\ system \quad (1.3)$$

3 Aspects to Optimise

An initial analysis was conducted to define aspects of the product and production system that could be improved and analysed by measuring the selected KPIs. A complete table of discussed aspects is included in Appendix D. The aspects in Table 3 have been targeted to improve system flexibility, quality, reliability and delivery.

Table 3: Aspects of the production system targeted in optimisation.

Area	Aspect	KPIs influenced
Manufacture	Machine operating time	Lead time
	Idle time	System utilisation, Lead time, WIP
	Number of machines	System utilisation, lead time, WIP
Assembly	Total time for assembly	Lead time
	Batch Size	Lead Time, WIP
	Skills of workers	Lead time
	Number of workers	Lead time
	Number of failed assemblies per 100	WIP, System Utilisation
Design	Number of parts in design	WIP
	Number of parts in assembly	WIP

To improve these aspects of the production system the following improvement methods are used:

- A mathematical formulation of the schedule optimisation problem. This allocates jobs to workers with an objective to maximise time spent on value-adding activities. This minimises waste through overproduction and hires a minimal number of workers to operate the factory.
- A revised machined part schedule is computed by evolutionary modelling using a genetic algorithm to reduce machine operation waste in idle time.
- Order-driven assembly in the assembly cell using a discrete event simulation. Improved batch sizing, worker skill level, and product redesign are analysed within this model.
- Implementation of quality-at-source methods within the assembly process to minimise waste in product reprocessing.

The interdependency between the selected KPIs will be considered when analysing changes to the current production system to allow holistic conclusions to be drawn about the most effective optimisation methods based on the level of investment *Acme* is willing to consider.

4 Proposed Improvements

4.1 Scheduling

This section describes the process of optimising the production schedule to meet fluctuating seasonal demand. At a high level, the optimisation objective is to maximise time spent on value-adding activities, minimise waste through overproduction, and hire a minimal number of full-time workers to operate the factory and meet demand. The baseline schedule's KPIs of System Utilisation (SU) and Work in Process (WIP) act as a benchmark for the optimisation.

Modelling assumptions and their impacts on the optimisation process with respect to *Acme's* business priorities are discussed. Next, a mathematical formulation of the schedule optimisation problem is described with a weighted objective function and 5 constraints that define valid schedules. The implementation of the problem in a MILP (mixed integer linear programming) solver, GUROBI (accessed through PuLP), is presented and the relaxation of constraint 2 due to resource limitations is explained.

The top 3 solutions to the LP problem, with the highest SU, are subject to sensitivity analysis. Stochasticity in the productive rates and demand are characterised by sampling from a Gaussian distribution around base cases. Finally, the improved setup and schedule are presented, and improvements over the baselines are quantified.

4.1.1 Problem Description

Aspects of the lean manufacturing methodology that can be optimised through scheduling include:

1. Meeting seasonal and fluctuating demand with JIT manufacturing, modifying the batch size
2. Increasing SU in value-adding activities, minimising idle time and workers
3. Reducing WIP and overproduction

A baseline schedule was derived using several assumptions discussed in Appendix E1, and component process timings shown in Appendix A, Tables A2-4. The results of the baseline schedule are summarised in Appendix E, Table E2.

This baseline meets the simplified demand requirement of 30,000 total assemblies per year but fails to maximise the capability of the factory's workers and machines, managing a best-case average SU of 0.39, with a corresponding average WIP of 205,000 components. Furthermore, the products are not manufactured with consideration for timing demand – this in turn locks up capital associated with producing, storing, and securing large quantities of products not ready for sale.

4.1.2 Model Description and Implementation

To develop a model of the system that could be described as a linear programming (LP) problem, a set of assumptions were adapted from the baseline schedule and are summarised in Appendix E1. These assumptions simplify the model, inevitably at the cost of the model's ability to clearly reflect the complexity of *Acme's* production system. The model aimed to capture key insights into where performance improvements with respect to SU and WIP can be gained. This can then inform future modelling exercises at a more granular level of detail. An LP model of the factory's annual schedule is described by Equations 2.1-2.6. Descriptions of the variables are provided in Appendix F.

The system describes a set of station operators whose working cycles are divided into sequentially executed time steps, each day of a 250 working day cycle. Each time step is an uninterruptible sub-task of station operation and also a basic scheduling unit.

An optimal schedule produces as many final products $a_{J_{MA}}$ as possible whilst minimising overproduction of all other parts. With the objective function formulation described by Equation 2.1, if all constraints are met, the optimal solution will tend to assign workers to be idle, instead of assigning workers to jobs that produce no value. This simplifies the calculation of SU and WIP.

In this model, each station is operated throughout the time step by the same operator – such that 'operator' and 'station' are analogous. The constraint that each worker can only carry out one job at any given time is implemented in Equation 2.2.

The average SU can be improved by organising fewer workers to carry out the most valuable tasks at the time they are required – the point of demand. The effect of a demand constraint, implemented as Equation 2.3, combined with an encoding of the dependency between components and assemblies in the model, implemented as Equation 2.4, creates an artificial, internal demand for each component. This ensures that each activity carried out is necessary to meet the product demand – forcing the production of useful components.

Equation 2.5 adds a constraint that forces a down-time $\tau_{jj'}$ to be observed after every change between jobs j and j', where j' is any job that can be carried out on the same machine as job j, other than j.

4.1.3 Objective Function

$$\max_{d,a,m,l} \; 5 * \sum_{o \in O^a} \sum_t a_{J_{MA},o,t} - \left(\sum_{j \in J^d} \sum_{o \in O^d} \sum_t d_{j,o,t} + \sum_{j \in J^a} \sum_{o \in O^a} \sum_t a_{j,o,t} + \sum_{j \in J^m} \sum_{o \in O^m} \sum_t m_{j,o,t} + \sum_{j \in J^l} \sum_{o \in O^l} \sum_t l_{j,o,t} \right) \quad (2.1)$$

subject to:

1. For any operator, at most one job can be in progress at a time t.

$$\sum_{j \in J^s} W^s_{j,o,t} \leq 1, \quad \forall\, s \in S, o \in O^s, t \qquad (2.2)$$

2. Daily demand must be met by the assemblies in inventory

The sum of all products (main assembly, MA) made must be greater or equal to the sum of the demand for all t

$$\sum_t \sum_{o \in O_a} a_{j,o,t} * P_j - \Psi_t \geq 0, \qquad \forall\, t, j = J_{\overline{\omega}}, \overline{\omega} = MA \qquad (2.3)$$

3. Job hierarchy and precedence

For each assembly $\varpi \in \Omega$, the number of assemblies that can be made cannot exceed the number of each available component that is a constituent of that assembly

$$\sum_{t}\sum_{s\in S}\sum_{o\in O_a} W_{j,o,t}^{s} * P_j - \sum_{t}\sum_{o\in O_a} a_{\varpi,o,t} * P_{\varpi} \geq 0, \qquad \forall\, \omega \in \Omega, j \in \omega, t \tag{2.4}$$

4. If a job starts in a station at a time interval t, no other job can start in the same station until after this job is finished $t + \alpha_j$ and an additional downtime period $\tau_{jj'}$, derived from [11]

$$\sum_{j'\in J^s/j}\sum_{t'=t+\varphi_j}^{t'+\tau_{jj'}} W_{j',o,t'}^{s} \leq M\left(1 - W^{s}{}_{j,o,t}\right) \quad \forall\, s \in S, o \in O^s, j \in J^s, t \tag{2.5}$$

5. Decision variables are binary

$$W_{j,o,t}^{s} \in \{0,1\}, \qquad \forall\, j, o, t, s \tag{2.6}$$

4.1.4 Solving the LP Problem & Post-Optimal Analysis

The mathematical model was translated into a Python software package [12] and used to generate optimal schedules using PuLP [13] as an interface to the PULP-CBC-CMD solver. The functions in this software package were then used to derive time-series values for SU and WIP. Before implementation, a synthetic schedule was generated in Microsoft Excel, and constraints were applied to validate the implementation approach that would be taken in Python.

Once implemented in Python, it became evident that the number of constraints in the original problem formulation made solving intractable with runtimes exceeding 2 hours per optimisation on available hardware – without converging to a solution. The constraint described by Equation 4 was a source of complexity that was necessarily removed from the model. For a problem with 5 die operators, 3 assemblers, 3 mill operators, and 3 lathe operators, the number of constraints was cut from 186,780 to 7,500. Performance was further improved by acquiring a license for GUROBI [14], a best-in-class LP solver. An example GUROBI log file for a solved scheduling problem can be found in Appendix G.

A bin-packing algorithm [15] was used to establish the minimum number of workers that would be required for each task. From this, it was determined that a minimum workforce of 5 die-machine operators, 2 assemblers, 2 mill operators, and 1 lathe operator (short-hand {5, 2, 2, 1}) could service an annual demand of 30,000 products, in absence of the daily demand constraint.

To determine exactly how many workers should be hired to operate the production system, and how to assign them to jobs throughout the production cycle, a grid search solved the LP problem for 36 combinations of workforces. The number of die-machine operators was iterated from 5 to 7, assemblers iterated from 2 to 4, mill operators from 2 to 4, and lathe operators from 1 to 3. The best performing solution with respect to SU was {5, 2, 2, 1}, scoring a mean annual SU of 0.72, an increase of 103% over the baseline average. Comparing this solution's WIP to that of the baseline, a reduction of average WIP from ≈200,000 to ≈70,000 can be gained. Visualisations were regularly used to inspect solver behaviour and optimal results. Excerpts of plots for {5, 2, 2, 1} are shown in Figure 3.

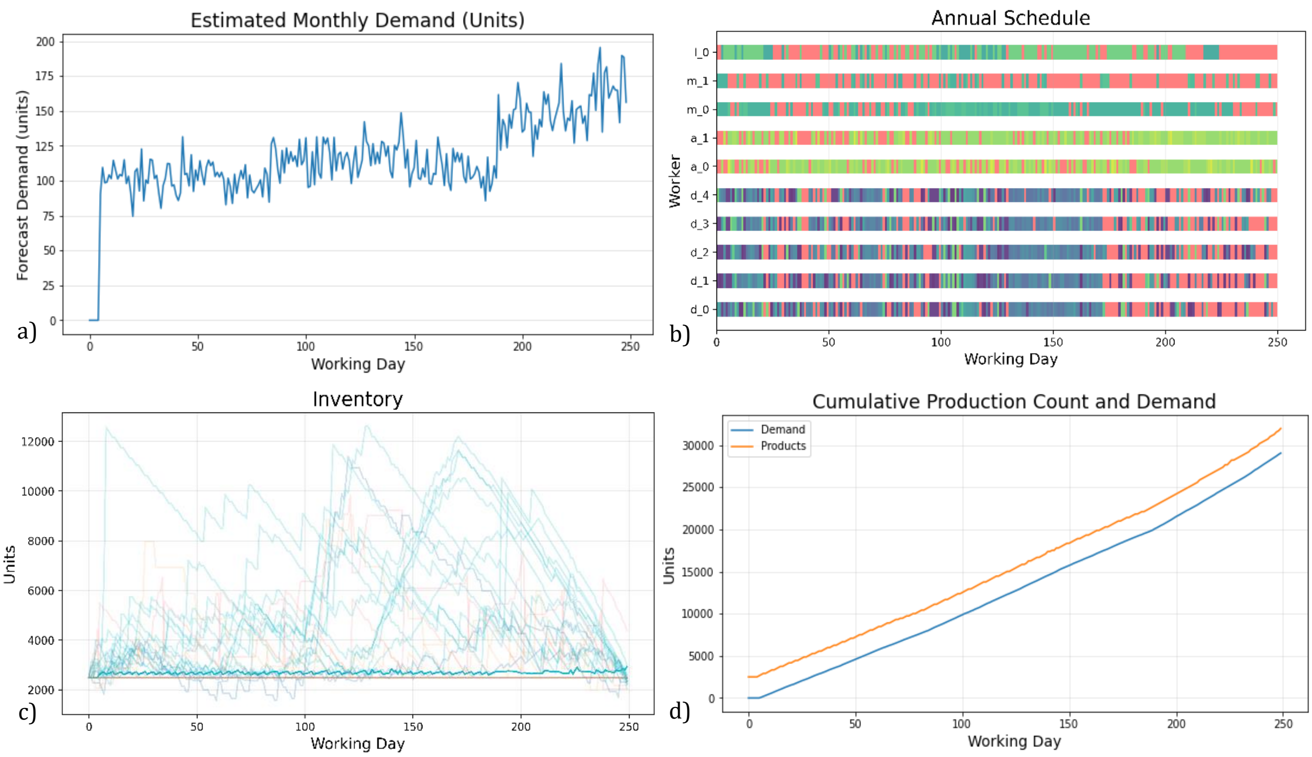


Figure 3: Plot excerpts from optimal worker combination {5,2,2,1} a) Shows a sample demand forecast with a 5-step demand delay. b) Shows an annual schedule. Each row represents a worker, with job allocation colour coded. Red indicates idle time. c) Shows unit counts for each component manufactured in the system. Product count is shown as a strong blue line hovering about the 2500 count. d) Shows cumulative demand and product count over the working year.

The three best-performing workforce combinations derived from the grid search were candidates for sensitivity analysis. Each candidate was a worker allocation: Candidate 1 = {5, 2, 2, 1}, Candidate 2 = {5, 3, 2, 1} Candidate 3= {5, 2, 3, 1}. The sensitivity analysis aimed to identify which of the candidates was robust to uncertainty in demand fluctuations and worker productivity; and which can result in optimal schedules. Each candidate was entered as solver input, with each combination of demand forecasts and productivity rates modified by sampling from a gaussian distribution: the details of this process are in Appendix H. Mean SU and WIP for each combination were then extracted, and their results were plotted.

Figure 4a clearly shows that Candidate 1 offers the best performance of SU, with a median of ≈ 0.74. Although recorded mean WIP varies significantly, the median is comparable between Candidate 1, and Candidates 2 and 3 in Figure 4b. As Candidate 1's SU and WIP is an improvement over the baseline and all tested worker combinations – it is suggested that the production system should operate with 5 die operators, 2 assemblers, 2 mill operators and a lathe operator if demand forecasts reflect this year.

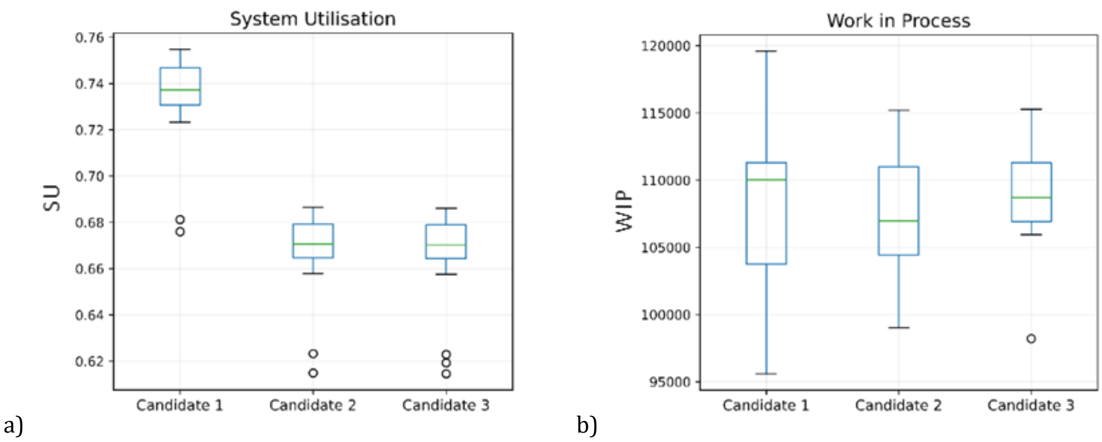


Figure 4: Results of sensitivity analysis on candidate workforces a) System utilisation and b) Work-In-Process.

4.2 Machining

4.2.1 Assumptions

The machining cell incorporates all processes requiring CNC milling, turning or rod bending. The baseline cell is assumed to have 1 of each machine, each operated by a single employee. Machined parts can be found in Appendix I Table I1 alongside their machining operations. Cylindrical steel bars are ordered at the required length and diameter for use in the product. Machining time is calculated via AutoDesk Fusion 360 CAM. The time for fixing raw material, changing tools and machine set-up (loading tools, setting datums and cleaning) is calculated using the Simplified Time Estimation Booklet for Basic Machining Operations [9]. It is assumed all timings can fluctuate between 90-110% of calculated times due to variation in cell productivity. It is assumed a machine set-up must take place when a machine changes the type of part it is manufacturing (e.g., 2a to 2b). It is assumed quick locking vices or collets are used to secure parts. Transfer times between machines or buffers have been ignored and deburring and anodizing are not considered. It is assumed the machining processes do not produce defective parts, and raw material stock is managed effectively such that there is never machine downtime due to lack of stock. The baseline process is sequenced on ascending part number. Parts are manufactured in batches of 2500, which is the monthly unit target for *Acme*. The timings for each operation or 'job' for a batch of 2500 alongside the part and Job ID can be found in Table I1 in Appendix I-Machining.

The baseline machining was modelled in Excel as a parallel machine scheduling problem, to investigate the cycle time and SU for 2500 units. The results are shown in Table 4, with a schedule diagram shown in Figure 5. The excel workbook can be found in Figure I1 in Appendix I.

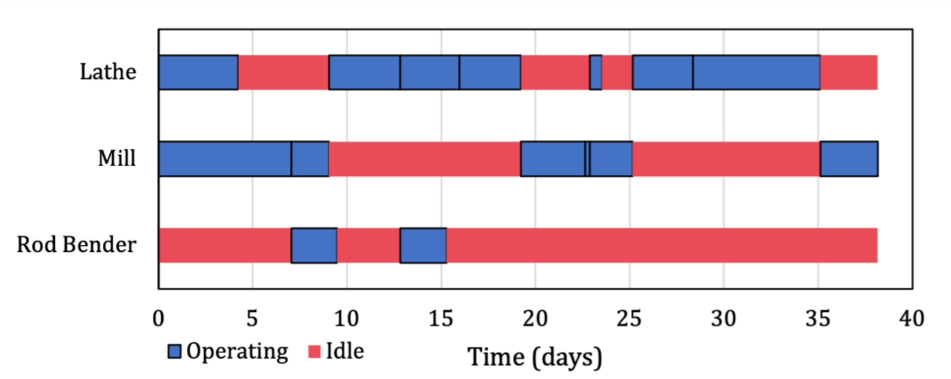


Figure 5: Baseline machining schedule, highlighting large idle time and therefore low system utilisation in the cell.

Table 4: Baseline KPI results from initial analysis of the machining cell.

Version	Cycle time (days)	Total idle time (days)	System utilisation
Baseline	38.158	66.582	0.418

4.2.2 Impact on KPIs

The machining cell manufactures a third of the parts in the entire system and currently cannot achieve demand, therefore improvements to the KPIs within the cell will have a significant impact on the global KPIs. Cycle time is investigated instead of lead time because the manufacturing cell operates 1 month ahead of the assembly; producing the predicted demand of parts for the next month. Reducing cycle time means that in the event demand exceeds the predicted demand, *Acme* will be more flexible to meet this surge. As shown in Table 4, the baseline SU is low within the cell. By reducing the idle time of machines, improvements to the SU will follow, this will have a knock-on reduction on cycle time; the lower bound of which is constrained by the maximum total machining time for an individual machine as shown in Appendix I– Machining Table I2.

4.2.3 Schedule modelling

To improve the cycle time and SU of the cell an Excel model was built, containing operation times for each part and the dependency of each operation, shown in Figure I1 Appendix I-Machining. For some parts, more than 1 process is required (e.g., milling then rod bending). The model is built to ensure that the jobs which are dependent on others cannot occur before the primary jobs. A flowchart for the model's logic process is shown in Figure 6. By using the evolutionary solver built into excel a genetic algorithm (GA) is built and iterations computed, varying the job sequence to output the lowest idle time. The GA approach has been used commonly for this problem (A. Costa, 2013). The results from this solution are shown in Figure 7 and Table 5 with detailed sequencing in Appendix I-Machining Table I3. Cycle time significantly decreased from 38.16 to 25.01 days and SU increased from 0.418 to 0.638.

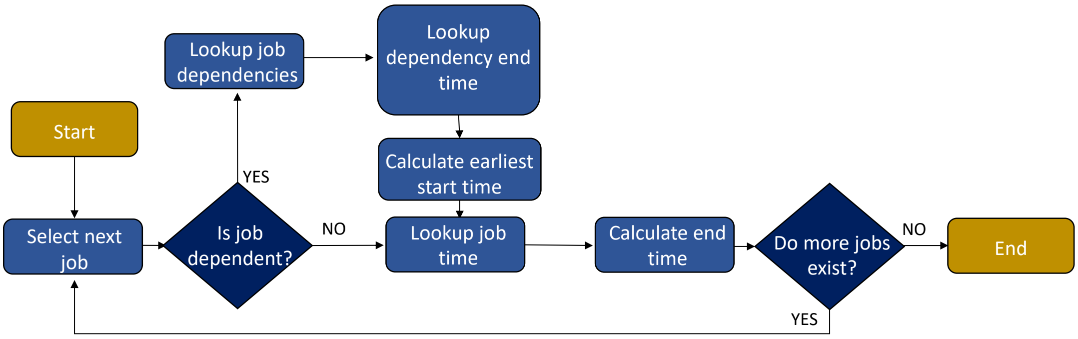


Figure 6: A flow chart to describe the excel model logic process.

4.2.4 Introduction of New Machinery into the system

Despite the significant improvement to lead time and SU, the scheduling does not achieve the target cycle time for 2500 parts in 20.8 days. This can be achieved by introducing an additional CNC Lathe to the cell. The output schedule of the new system is shown in Figure 8 and the impact on SU and cycle time is given in Table 5.

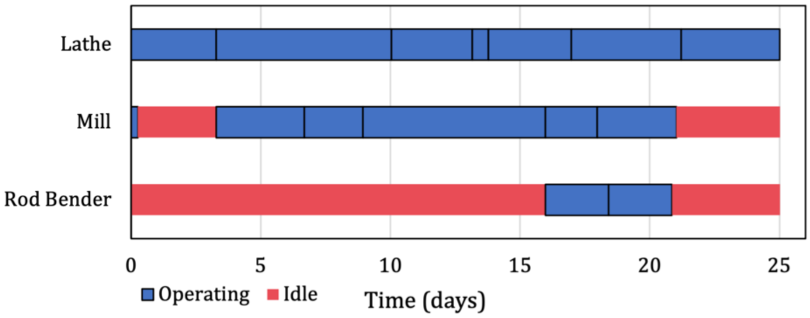


Figure 7: Machining operating schedule post evolutionary modelling and improvement.

Table 5: Comparison of the impact of improvement to the machining cell on cycle time, total idle time and system utilisation.

Version	Cycle time (days)	Total idle time (days)	System utilisation
Baseline	38.158	66.582	0.418
Improved Sequence	25.011	27.139	0.638
Additional Lathe	18.007	24.135	0.665

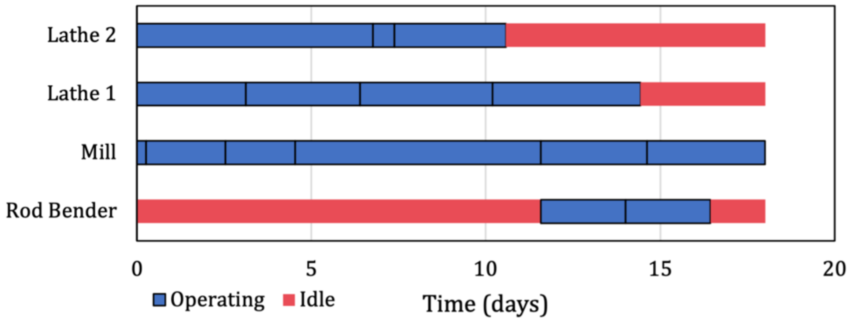


Figure 8: Machining operation schedule post introduction of additional lathe.

4.2.5 KPI Results

The results of the evolutionary sequencing model using an additional lathe in Table 5 have significantly improved the performance of the machining cell. SU increases from 0.42 to 0.67 and cycle time decreases from 38.16 to 18.01 days. WIP has not been analysed in detail in the machining. Given the impacts on cycle time, the throughput could be increased to prepare for higher-demand months which would increase WIP.

4.3 Assembly

The existing system has two workstations with one assembly worker at each station. The first worker oversees sub-assemblies and transfers them to the second worker completing the main assembly. The entire assembly is completed by hand. The current system contains waste in waiting time, product reprocessing, inefficient processes, transportation, and employee potential. However, a small number of lean manufacturing concepts are already employed including standardized work charts at the assembly station and Poka-yoke scanning operations to ensure parts are in the correct buffer. It is proposed additional concepts are implemented into the system including:

- Training employees to maximise employee potential for optimum assembly fabrication time.
- A product redesign to simplify the assembly process and/or reduce part count

Order-driven assembly: the current system produces assemblies at a standard rate of 15 per hour to achieve the 2500/month target. By transitioning to an order-driven process, batches of assemblies will only be started once an order arrives in the system. This aims to reduce WIP and demonstrate flexibility to order demand. Additional changes within the systems are included:

- Changing batch sizing of assemblies to reduce transport delays and component interdependencies.

Quality-at-the-source: The current system relies on quality assurance checks at the end of the assembly to inspect quality into the final product with no error-proofing methods during the assembly. This results in a high volume of unnecessary handling of reprocessed products adding no value. It is proposed to build-in quality at the source during the assembly process to reduce waste in reprocessing and waiting. The following methods are evaluated:

- Implement procedures at workstations to inspect the quality of each completed assembly stage.
- Error-proofing methods including visual systems to ensure the correct order of assembly.

4.3.1 Model Description

The assembly process can be modelled analytically considering cycle time defined as the time one assembly is in the system from an initial group of parts to a complete product assembly, Equation 3.1

$$PA = \sum_{i=1}^{i=n} SA + \sum_{i=1}^{i=m} MA + \sum_{i=1}^{i=q} QA + \sum_{i=1}^{i=t} TR + \sum_{i=1}^{i=w} W + \sum_{i=1}^{i=r} RP \tag{3.1}$$

Where PA is the product assembly time in seconds, SA is a given sub-assembly fabrication, n is the number of sub-assemblies, MA is a given main assembly fabrication, m is the number of main assemblies, QA is a given quality assurance, q is the number of quality assurance checks, TR is a given transfer time between workstations, t is the number of transfers, W is a given waiting time before a workstation, w is the number of queues in the system, RP is a given reprocessing time (this can be zero if no faults), and r the number of potential reprocessing stages.

A discrete event simulation model in AnyLogic is used to model the assembly system. The system contains 5 sub-assemblies and a 7-stage main assembly line. Each fabrication stage (MA , SA) is modelled as a delay with a PERT (program evaluation review technique) distribution. Depending on skill level workers can perform a task between an optimistic maximum or pessimistic minimum about a modal value using data taken from assembly estimations using a physical product model scaled by the batch size. Calculations have been included in Appendix K.

A delay is associated with the transfer of parts (TR) that is repeated for each batch. Parts wait for workers in a queue before the task can be completed and the time (W) is calculated by AnyLogic. The main assembly requires completed sub-assemblies before the next stage can be completed. All assembly stages complete the same batch size of tasks. A gate can be used to control the flow of products and model a make-to-order system. A simplified flow diagram is shown in Figure 9.

Learning is considered as a percentage multiplier of the delay according to the number of parts completed. Quality assurance and any reprocessing delays are performed at the end of the assembly process by the main assembler. Quality assurance (QA) inspections are assumed a triangular distribution with a mode value of 15s +/-5s. A predicted probability of product failure is estimated for reprocessing (RP) as 18 in 100 assemblies with a delay equal to the total assembly fabrication time. Section 4.3.5 contains a detailed discussion of this reprocessing assumption.

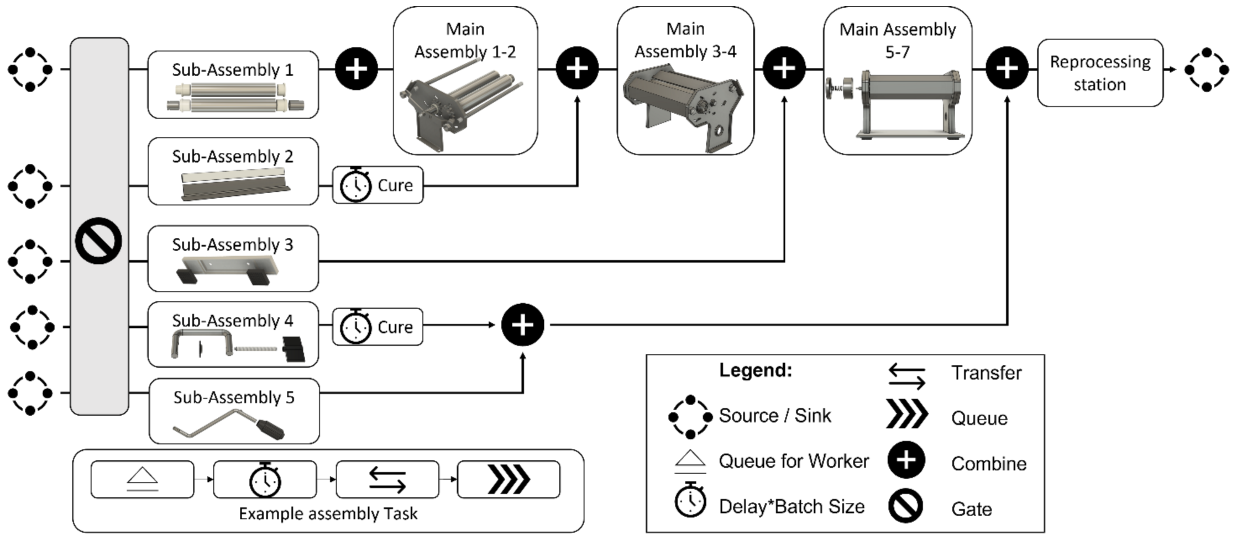


Figure 9: AnyLogic flow chart of the Assembly

The modelling completed in this section measures the lead time, WIP and SU for assembly in isolation from manufacturing. In the baseline, it is assumed the manufacturing system produces parts a month ahead before assembly so that assembly can be started at the beginning month. Within the assembly system, the lead time is considered as the time taken for a random event order (a triangular distribution equating to 2500/month) to be fulfilled by the assembly system (comparison of absolute times). Bulk storage of manufactured parts is considered easier than storage of partially completed assemblies and sub-assemblies due to geometric constraints. As such modelling focuses on WIP within the assembly system and excludes the bulk stored machined parts and completed assemblies which are ready for shipment.

4.3.2 Assembly Worker Training Preliminary Investigation

Assembly workers learn their tasks by executing them. As they repeat the same tasks their experience level increases, and this reduces the time to complete specific tasks. This phenomenon was first introduced by Wright and coined 'the learning effect' [16]. Equation 3.2. estimates the learning curve of assembly workers when hired.

$$C_x = C_1 \cdot x^{-b} \tag{3.2}$$

C_1 is the time taken to complete the first assembly, x is the current assembly number, C_x is the time taken to complete the current assembly, and b is the learning coefficient. Research has found that there is a 27% or 20% reduction in first assembly time when physical or virtual training is completed respectively [17]. For the hand-crank pasta maker, the time spent physically fabricating one assembly has been estimated as 371s. The steps and skill level have been considered to calculate the estimated fabrication time of each stage and have been included in Appendix J.

To assess the impact of training at a surface level a Monte Carlo simulation is carried out assuming a uniform distribution of learning coefficients for trained and untrained workers, where b=0.01-0.04 and b=0.05-0.1 respectively, and a 27% reduction in first assembly time for trained workers. Figure 10 shows that based on these assumptions the trained worker reaches an optimum fabrication time (PA) after 200 assemblies compared to 600 or more assemblies when not trained. The scenario additionally considers hiring a new assembly worker after 625 assemblies. A temporary reduction in fabrication time occurs because the new worker must learn by executing the tasks increasing the average time spent fabricating one assembly. Hiring new workers could be necessary and training these workers reduces the impact of the learning effect and wasted employee potential in the assembly system.

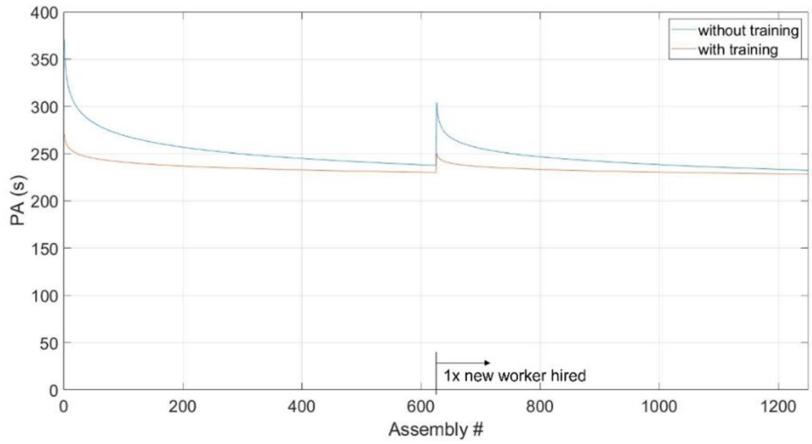
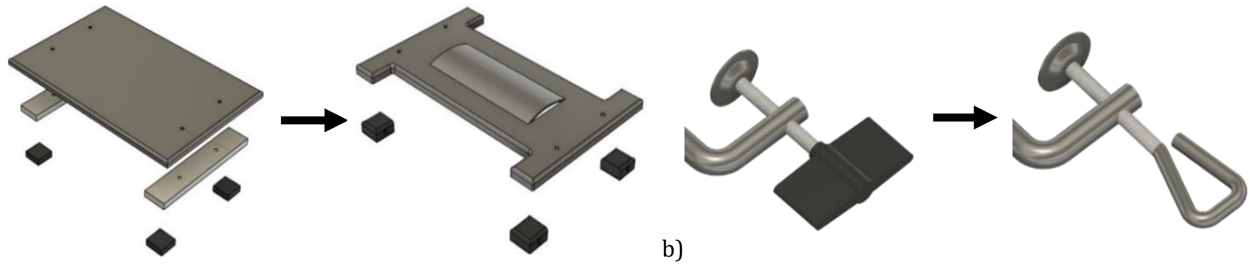


Figure 10: Simulation of assembly fabrication time based on number of assemblies completed and training. PA is the Product Assembly Time

4.3.3 Product Redesign

Five product redesigns are proposed that simplify the assembly process and/or reduce part count. These areas have been identified as critical to lead time with the potential for modification.

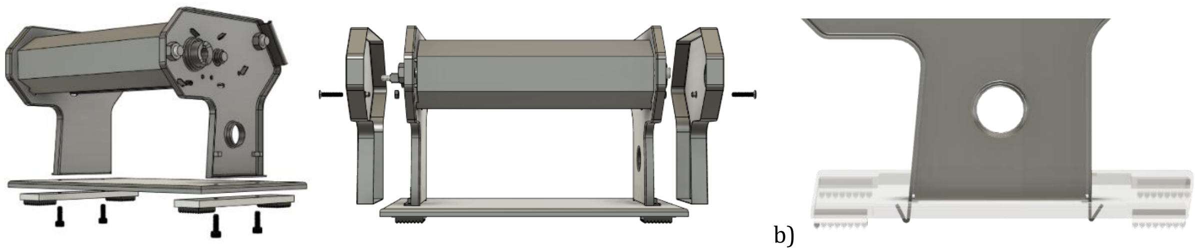
1. Absorb metal feet into the base plate – reduce part count and the number of assembly stages. Impact assembly stages: MA5, SA3
2. Clamp redesign to all metal - reduces part count by 1 and no adhesive delay. Impact stage: SA4



a) b)

Figure 11: Present to lean a) base redesign and b) clamp redesign.

3. Change 6 screws to snap fits on the legs and outer casing. Reduces part count and snap-fit incorporates mistake proofing. Impact stages: MA5, MA6



a) b)

Figure 12: a) Present screw fixed product and b) The proposed snap fit design (legs shown here)

4. External push-on fastener to achieve the same function as a washer – saves time locking the washer and reduces potential error when the washer is not locked correctly. Impact stage: MA1.
5. Press fit sheath includes a physical endpoint requiring less worker precision. Impact stage: SA1

After the lean product design changes are implemented the product assembly time is calculated using Equation 3.3, where C is the lean transformation coefficient.

$$LeanPA = C_{SA} * \sum_{i=1}^{i=n} SA + C_{MA} * \sum_{i=1}^{i=m} MA + \sum_{i=1}^{i=q} QA + \sum_{i=1}^{i=t} TR + \sum_{i=1}^{i=w} W + \sum_{i=1}^{i=r} RP \tag{3.3}$$

Updated lead times using a lean design are provided in Table 6. Calculations of estimates have been included in Appendix J.

Table 6: Present-state vs Lean-state sub/main assembly times.

Stage	Present-state assembly		Updated Lean-state assembly	
	Time (s)	Skill level	Time (s)	Skill level
MA1	36	3	20	3
MA2	32	2	No change	
MA3	26	1	No change	
MA4	20	2	No change	
MA5	54	1	20	1
MA6	36	2	10	1
MA7	21	2	No change	
SA1	70	3	40	2
SA2	30*	3	No change	
SA3	10	3	0	-
SA4	31*	3	16	2
SA5	5	1	No change	

*plus 500s adhesive cure.

A significant degree of uncertainty is associated with these estimated times. Stochastic modelling is beneficial when considering changing behaviour or unpredictable events in production facilities. The product redesign will be analysed using the AnyLogic model in the next section.

4.3.4 Make-to-order system, trained workers, Batch changes and product redesign.

The baseline system produces assemblies at a rate of 15 internally started orders per hour, to achieve a total output of 2500 per month. The make-to-order system has 2500 orders randomly distributed throughout the month and a batch of assemblies is only started once an order is made. The baseline batch size is 10. At each assembly stage, a batch of every action is performed before the worker can perform a different assembly task.

The make-to-order change was implemented using the additional gate in the assembly AnyLogic model preventing agents from entering the system until the number of orders was greater than the number of assemblies being produced (zero at the start).

An initial variation on the assembly batch sizes was carried out to find the most suitable batch size within the baseline system and altered systems for WIP and Lead time. The batch sizes considered are 1,2,5,10,15. Within the system, a constant transfer for each batch is included independent of batch size.

Trained workers were modelled as having a 15% improvement to the starting assembly time this is lower than the achievable 20% and 27% obtained through virtual and physical training respectively. C_1 Equation 3.2 equals $0.85*C_{baseline}$ and is equivalent to the worker having already completed 58 assemblies (around 1 day of assembly work).

A Monte Carlo simulation with 200 replications was run for each variation of the model for the first 2 weeks of the month. WIP is calculated every 3 minutes and the average taken over time taken to complete 1400 assemblies. The median of the average lead time and the mean of the average WIP are found for the 200 replications and shown in Table 7 (an example of the graphical representations is shown in Appendix M Figure M1). The mean and median are deemed representative comparative values for a summary comparison with the baseline values outlined in bold.

Table 7: Comparison of Assembly changes for different batch sizes

KPI		Batch Number				
		1	2	5	10	15
Median Lead Time (Minutes)	Baseline	652	350	360	**480**	490
	Make to order	1170	780	430	460	510
	Trained Workers	360	315	330	388	414
	Product Redesign	295	300	375	385	450
Mean WIP (Parts)	Baseline	770	505	475	**505**	550
	Make to Order	970	1290	890	1055	1250
	Trained Workers	430	425	430	400	460
	Product Redesign	470	455	415	435	422

Changing the batch size has positive improvements for the baseline system. Changing to 5 batch assemblies reduces assembly lead time by 25% and shows a minor improvement for WIP. When a batch size of 1 is considered, downtime decreases, and the assembly workers can no longer keep up with the desired throughput rate of 15 per hour.

Transitioning to a made-to-order assembly system does not provide significant improvements that cannot be achieved with small changes to the baseline system. Due to constraints in the system where main assembly worker downtime reaches <5% a bottleneck is created and, the made-to-order system is not able to keep up with demand. And achieves poorer WIP due to these constraints.

SU has been calculated as an average of the assembly worker utilisation which is time spent adding value assembling the product. When considering assembly workers, a higher SU for no lead time or WIP gain is not necessarily considered an improvement. Higher SU on its own may cause fatigue and impaired cognitive function, which is likely to increase worker error requiring more reprocessing and a worse lead time and WIP [18] [19].

Training workers prior to the first assembly shows a significant improvement to lead time (up to 35%) and WIP (up to 20%) across all batch sizes and notably causes the 1 batch system to become stable, with no bottlenecks at 2 weeks. As such training, is strongly recommended for new workers.

Implementing the product redesign similarly shows an improvement with all batch sizes for average lead time (up to 40%) and WIP (up to 18%).

4.3.5 Quality Assurance and Product Reprocessing

When assembling the hand-crank pasta maker the probability of assembly worker errors must be considered. Using 'Fuzzy Sets Theory' and 18 expert opinions Sagnak (2020) concluded most of the waste at the kitchenware manufacturing company (50%) was due to reprocessing repackaged products [7]. Further, it was suggested 32% of reprocessing was due to errors in the assembly line. Considering this data, *Acme*'s current quality assurance and reprocessing system are evaluated. Reprocessing encompasses identification of the fault, disassembly, replacing/correcting defective components, and reassembly. Figure 13 displays the existing quality assurance and reprocessing system.

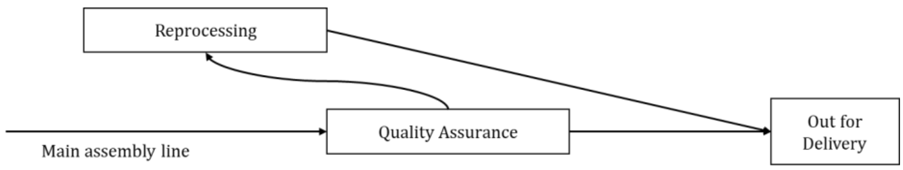


Figure 13: Existing quality aaurance and reprocessing system.

It is proposed to build-in quality at the source during the assembly process with the aim of reducing waste in reprocessing and waiting. Firstly, a process redesign is proposed that implements procedures at workstations to inspect quality of the previous assembly step. The schematic of the proposed quality-at-source system redesign is shown in Figure 14.

A discrete event simulation is set up to analyse the impact of the system redesign on the three KPIs. The baseline AnyLogic model was utilized with the same constraints, delay times, learning rate, part input rate and consumer demand pull at a mode value of 2500/month.

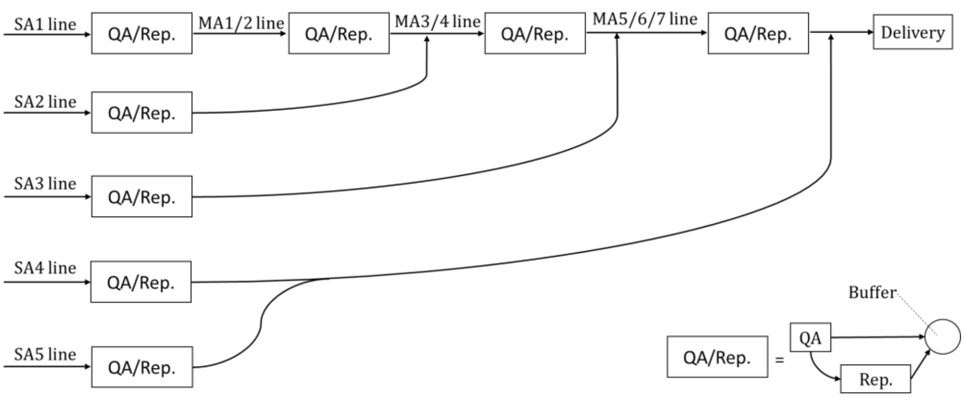


Figure 14: Proposed quality-at-source system.

The current probability of product failure in the assembly system is unknown. Product failure has been defined as a lack of product functionality. To estimate the probability of product failure potential errors were identified and the associated probability was assumed relative to the assembly stage skill level required. Appendix L Table L2 includes the identified assembly errors and relative probability. Errors in the assembly line are assumed to be mutually exclusive therefore multiple errors within an assembly stage or across assembly stages are estimated as the sum of the individual probabilities.

The delay time in the reprocessing process has been assumed to have the same distribution as the time taken to assemble each relative assembly stage. For example, reprocessing time after assembly line MA1/2 would have a mode value of 36s plus 32s. The sum is distributed as a PERT distribution according to the highly skilled job range 10% faster or 30% slower than the mode.

The baseline system completes reprocessing at the end of the assembly line making the mode time delay 371s and the mode probability of failure at the final product is 18%. The quality-at-source system distributes the quality assurance delay equally between assembly stages. Reprocessing time and probability of failure are calculated at each stage using the method previously stated.

The impact of the quality-at-source (QAS) process redesign is compared to the existing system and an alternative baseline in which one new worker is hired solely to complete the quality assurance and reprocessing. A Monte Carlo simulation is run in AnyLogic with 50 replications to achieve the subsequent outputs. Figure 15 displays the Work-In-Process in the system over one week. To generate this plot WIP data was collected every minute. Mean values were obtained from the model replications and each point on the plot is the average of the hour (60 points). Figure 15 b shows the output of lead time for the first 700 orders taken as the mean value of 50 simulation replications.

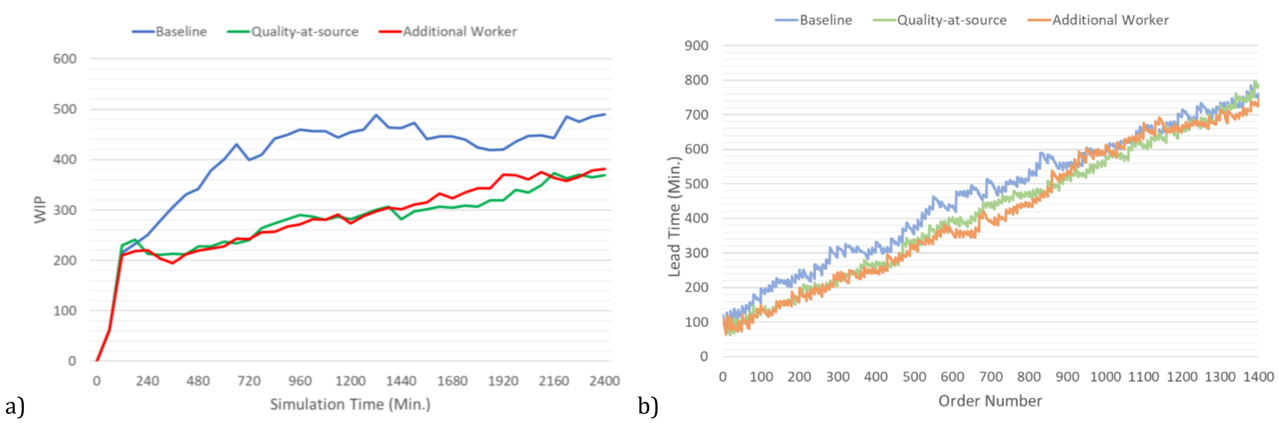


Figure 15: Quality checking process redesign impact on a) Work-In-Process over 1 week and b) Lead-time for 1400 orders.

The response of the additional worker system and the QAS system are comparable from the measurements of WIP and lead time. In Figure 15 a, a similar transient response is seen between the QAS system and the additional worker system as the WIP plateaus at 200 assemblies in the system. After 120 minutes the WIP grows steadily. For the baseline model, the WIP increases rapidly for the first 700 minutes to plateau around 450 assemblies. A lower WIP has clear benefits in reduced waste in waiting for parts in queues for assembly. Following the first week of assembly WIP continues to rise towards the maximum capacity of the system.

Figure 15 b shows lead time for the first product order is 119 minutes for the baseline, 109 minutes for the with an additional worker and 102 minutes with the QAS redesign. Lead time grows initially at a slower rate compared to the baseline. At 900 orders or 1 to 2 weeks of production lead times show little difference. Hence, a minor improvement in delivery is observed using the QAS redesign as there is a reduction in the rate of increase in lead time over the first week of assembling. None of the current processes reach a steady state in lead time over one month of operation. An ideal lean system would plateau to a steady state after an initial transient period.

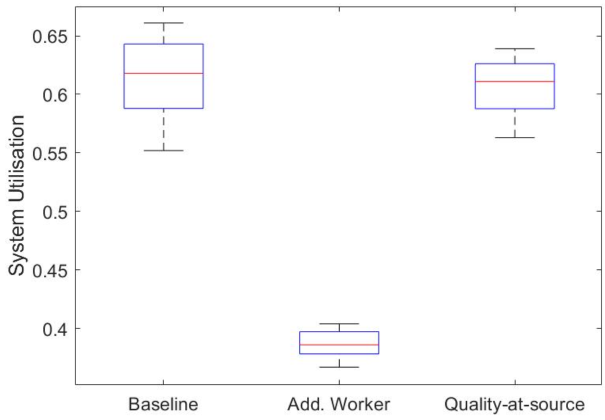
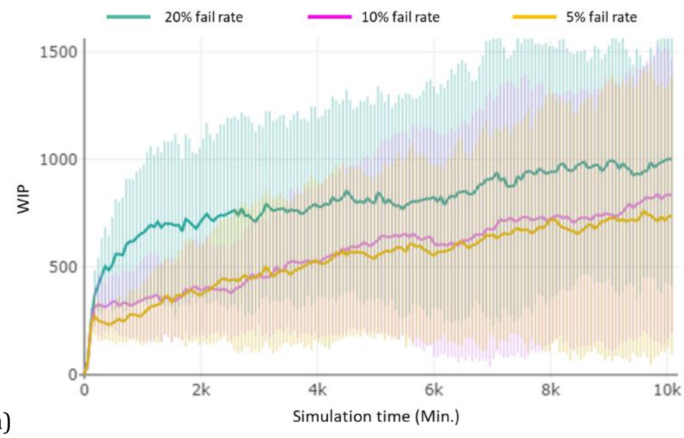


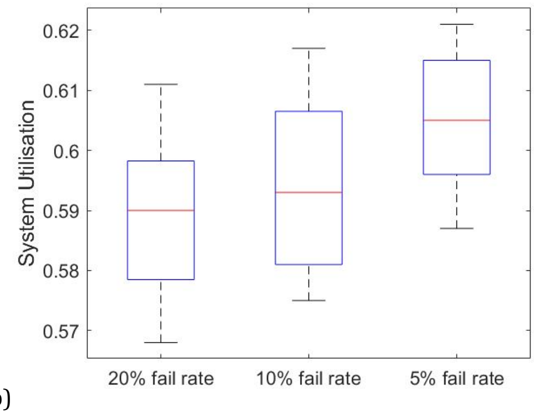
Figure 16: Process design system utilisation

Reprocessing is not considered a value-adding process in the system and does not contribute to SU. Figure 16 displays the SU for each model. The QAS redesign has a comparable SU to the baseline model and 22.5% greater SU than the additional worker baseline using the median values. This data suggests that the improvements seen by hiring an extra worker can be achieved with two workers and a quality-at-source redesign. These improvements include reduced WIP and minor improvements in lead time that maintains a high SU level.

To further reduce the impact of reprocessing and errors in the assembly line the impact of Poka-Yoke error-proofing methods including a visual system to indicate the order of assembly and worker training is evaluated. Informed by research a failure reduction of 50-90% is possible using error-proofing methods in assembly [20], [21]. The quality-at-source system is tested with an average probability of errors across the system as 20%, 10% and 5% demonstrating the impact of error proofing. Figure 17a shows a Monte Carlo simulation run in AnyLogic with 50 replications varying these parameters.



a)



b)

Figure 17: Varying the average number of failed assemblies per 100 produced and measuring a) WIP and b) system utilisation over 1 month at a medium-level demand pull (mode 2520 orders/month).

Figure 17a shows a significant reduction in WIP over one month when there is a 50% reduction in errors from an initial 20% fail rate. However, this reduction in WIP is limited once the system is operating at under 10% product failures. This suggests that error proofing need only be considered if the current manual pasta maker assembly system operates at above 10% probability of failure. Change in failure rate had little to no effect on lead time. The quality-at-source system analysed previously has an average probability of error of 2.2% across the system using the probability assumptions in Appendix L. At this failure rate, error-proofing methods would have minimal impact on improving the system.

Figure 17b demonstrates an improvement in SU as the probability of error or product failure decreases, and more time is spent by workers adding value to the product instead of reprocessing faulty products. In the lean system, wasted time should be minimised and reprocessing time should be limited. However, at this medium level demand the statistical significance is not seen as the quartiles overlap between the data sets. To investigate this a test was completed at a high-level demand by doubling the consumer order rate to a mode of 30 per hour. Here the assembly workers work at maximum capacity and reducing the failure rate from 20 in 100 to 10 in 100 sees and SU increase of 7.6%. A 12.6% increase in SU is seen with a further drop to 5 in 100 failures/errors, evidenced in Appendix L Figure L1.

The analysis in this section has highlighted the impact of built-in quality checks within the manual pasta maker assembly system. Measured KPIs WIP, lead time and SU collected using discrete event Monte Carlo simulations allowed assessment of a process design and sensitivity analysis to error proofing. The results have informed the following recommendations:

- Implement a quality-at-source process redesign.
- A survey to determine the number of failed assemblies in each production line. If this value is higher than 10% implement Poka-Yoke methods to reduce errors as this will reduce WIP.

5 Improvement Impacts

The proposed improvements are compared in Table 8. The most successful improvements have multiple plus signs and are highlighted in green, and an estimated transition cost is provided. The improvements are most successful at targeting SU across the production system and lead time within assembly.

Table 8: Comparison of proposed system improvements

Legend: + : Improvement (number shows scale of improvement); - : worse performance; . : not considered or no change; £ : cost (exponential)		Comparison of proposed improvements				
		Lead Time/ *Cycle Time	**System Utilisation**	**WIP**	**Est Cost**	**Additional impacts on lean manufacturing principles**
Manufacture	Machining Scheduling	(++)*	+++	.	£	.
Assembly	Product Redesign	+++	.	++	££££	(-) Increased manufacturing complexity
	Worker Training	+++	.	++	££	(+) upskilling of workers
	Batch Sizing	++	.	+	£	.
	Make assemblies to order	-	.	-	£	.
	Reprocessing	.	+	++	££	(+) Fewer workers required
Manufacture and Assembly	System Scheduling	.	+++	.	£	(+) workers minimised

System Utilisation - Improving system utilisation increases the value-adding time associated with machines or workers. The elimination of idle time within the system minimises waste aligning with the lean approach. Both the machining cell and system-wide scheduling changes achieve reduced idle time increased SU by 0.24 (to 0.66) and 0.37 (to 0.75) respectively. Machining scheduling is necessary to achieve the target 2500/month assembly components within 25 working days which would include worker overtime. An additional lathe is needed to achieve machining targets within the 21 working day month that accounts for holidays.

Within machining, the reduction in idle time enables the production of all parts within the month and improves cycle time and throughput capability allowing *Acme* to achieve a higher demand and reduce the time parts are required to be machined prior to assembly. The manufacturing system is currently unable to transition to a lean system due to dependencies and still requires parts to be manufactured in bulk before assembly can begin.

Lead Time - Improvements to lead time are achieved within the assembly system. Reducing lead time enables assemblies to reach customers more quickly, the proposed changes enable this without reducing quality or increasing the failure rate. The external delivery system may require changes to fully realise the improvements in lead time. The product redesign can achieve close to a 40% reduction in lead time although these changes may require significant investment and retooling. A small change from batches of 10 to 5 assemblies achieves a 25% reduction in lead time within the assembly system. Worker training should be prioritised for all new workers with lead time improvements of up to 35% and it can stabilise all systems within the first 2 weeks. It is a much lower-cost alternative to product redesign and is useful for creating flexibility within busy seasons of demand. Once a worker has already been in the assembly cell these training improvements will be less significant.

Work in Process - Despite Just in Time and lean manufacturing practices proposing make-to-order systems as methods of reducing part storage and WIP the assembly system is not able to cope with the make-to-order constraints. As assembly bottlenecks are reached and the system becomes unstable with WIP increasing until the maximum storage capabilities of the system are reached. The improvements to WIP are achieved by reducing the time in the assembly system. These are caused by shorter cycle times with product redesign reducing average WIP by up to 15%, training workers reducing average WIP by up to 20% and batch changes reducing average WIP by up to 5%. A quality-at-source (QAS) system reduces the rate of increase of WIP towards the system capacity and error-proofing can minimise the number of assemblies being reprocessed. These reductions mean more storage can be devoted to bulk parts or higher-value complete assemblies before delivery. If errors within assembly are above 10% error proofing methods should be considered in assembly to achieve further WIP improvements.

6 Recommendations

Our recommendations based on *Acme'*s future business scenarios are shown in Table 9. The lowest cost change recommendations can be implemented without an extended transition period. These are recommended for all levels of investment and can be implemented immediately. If the business can only implement one change at a low cost, machining scheduling or system scheduling should be prioritised due to the bottlenecks in machining.

Table 9: Recommendations for system changes in three scenarios.

Scenarios	Capital	Time available to implement	Suggested system changes
Improvements to the system that require minimal or no funding.	£	Immediate, (No downtime)	Machining Scheduling System Scheduling Batch Sizing New worker training Quality-at-source process
Improvements over time, medium cash flow	£££	3 Months, (Minimal downtime)	+ Additional Lathe +Error proofing system if failures are high
Expanding business, High capital investment received.	££££	6 Months, (Some downtime Acceptable)	+ Additional Lathe + Product Redesign

7 Future Work

Limitations exist within the current models and hence future work should be completed to account for limits and provide comprehensive analysis. We recommend the following areas should be targeted:

- Scheduling - Building richer models by removing modelling assumptions and using sales data to improve forecasted demand trends and streamline production.
- Machining – Investigate using a combined Mill and Lathe, this would reduce setup times but require a large initial investment and redesigning of machine operations.
- Assembly – Improved integration with the manufacturing cell to reduce bulk part storage prior to assembly and enable a leaner system.
- Transfer time and storage- Investigate the transfer time and/or storage between stations. Focus on making a lean transfer between manufacturing and assembly.

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Appendix A – Baseline Production System

Table A1: Production system inputs, part processing and outputs.

Inputs		Manufactured in house			Outputs
Raw materials	**Standard components**	**Plastic processing**	**Steel bar processing**	**Steel sheet processing**	**Assembly**
Stainless steel bars	Spring	Hank crank handle	Support shafts	Casing	Pasta maker
Stainless steel sheets	M6 bolts	Clamp control handle	Adjustable shafts	Legs	Clamp
PVC grains	Roller tubes	Roller stoppers	Clamp main body	Base	Hand crank
Nylon grains		Feet: Plastic	Hand crank	Washer	
		Roller separator	Gear mechanism	Feet: metal	

Table A2: Component manufacturing processes, process timings and raw material for Parts 1A-3A. Continued in Table A3 & A4.

Baseline Manufacturing Processes										
Group	ID	Model	Component	Stock	Process	Machine	Time per process (s)	Total time (s)	Lower bound (s)	Upper bound (s)
1	A		Base	Steel Sheet	Transport to station from storage	-	2.72			
					Shear to perimeter	Shear die	15			
					Transfer	-	15			
					Hole punch	Punching die	15			
					Transfer	-	15			
					Draw into shape	Drawing die	15			
					Transport from station to storage	-	3.2	80.92	72.828	89.012
1	B		Foot	Steel sheet	Transport to station from storage	-	2.72			
					Shear to perimeter	Shear die	15			
					Transfer	-	15			
					Hole punch	Punching die	15			
					Transfer	-	15			
					Draw into shape	Drawing die	15			
					Transport from station to storage	-	3.2	80.92	72.828	89.012
1	C		Foot Plastic	PVC pellets	Transport to station from storage	-	2.72			
					Injection Moulding	Injection Mould	57.286			
					Transfer	-	15			
					Cut sprues and runners	-	48			
					Transport from station to storage	-	3.2	126.206	113.5854	138.8266
2	A		Clamp main body	10mm Ø steel cylindrical rod	Transport to station from storage	-	2.72			
					Machining total set up/removal time	-	2.16			
					Drill hole	CNC Mill				
					Tap hole	CNC Mill	80			
					Mill notch	CNC Mill				
					Bend to shape	CNC Rod bender	27			
					Transport from station to storage	-	3.2	115.08	103.572	126.588
2	B		Clamp threaded shaft	6mm Ø steel cylindrical rod	Transport to station from storage	-	2.72			
					Machining total set up/removal time	-	1.82			
					Cut end detail	CNC Lathe				
					Thread	CNC Lathe	47			
					Transport from station to storage	-	3.2	54.74	49.266	60.214
2	C		Clamp stopper	Steel sheet	Transport to station from storage	-	2.72			
					Shear to perimiter	Shear die	15			
					Transfer	-	15			
					Draw into shape	Drawing die	15			
					Transfer	-	15			
					Hole punch	Punching die	15			
					Transport from station to storage	-	3.2	80.92	72.828	89.012
2	D		Clamp control handle	PVC pellets	Transport to station from storage	-	2.72			
					Injection mould	Injection Mould	57.286			
					Transfer	-	15			
					Cut sprues and runners	-	48			
					Transfer	-	15			
					Tap hole	Pillar drill				
					Transport from station to storage	-	3.2	141.206	127.0854	155.3266
3	A		Hand crank	8mm Ø steel rod	Transport to station from storage	-	2.72			
					Machining total set up/removal time	-	3.99			
					Make cuts for key and notch	CNC Mill	22			
					Transfer	-				
					Add chamfer	CNC Lathe	42			
					Transfer	-				
					Bend to shape	CNC Rod bender	27			
					Transfer	-				
					Transport from station to storage	-	3.2	100.91	90.819	111.001

Table A3: Component manufacturing processes, process timings and raw material for Parts 3B-6D. Continued from Table A2 and in Table A4.

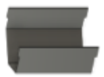
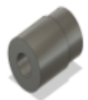
3	B		Hand crank handle grip	PVC pellets	Transport to station from storage	-	2.72			
					Injection mould	Injection Mould	57.286			
					Transfer	-	15			
					Cut sprues and runners	-	48			
					Transport from station to storage	-	3.2	126.206	113.5854	138.8266
4	A		Legs (4 unique components of similar size)	Steel sheet	Transport to station from storage	-	2.72			
					Shear to perimeter	Shear die	15			
					Transfer	-	15			
					Hole punch	Punching die	15			
					Transfer	-	15			
					Draw into shape	Drawing die	15			
					Transfer	-	15			
					Bend tabs	Bending die	15			
					Transport from station to storage	-	3.2	110.92	99.828	122.012
5	A		Cover A	Steel sheet	Transport to station from storage	-	2.72			
					Shear to perimeter	Shear die	15			
					Transfer	-	15			
					Bend x3	Bending die	15			
							15			
					Transport from station to storage	-	3.2	65.92	59.328	72.512
5	B		Cover B	Steel sheet	Transport to station from storage	-	2.72			
					Shear to perimeter	Shear die	15			
					Transfer	-	15			
					Bend x2	Bending die	15			
					Transport from station to storage	-	3.2	50.92	45.828	56.012
5	C		Cover C: metal	Steel sheet	Transport to station from storage	-	2.72			
					Shear to perimeter	Shear die	15			
					Transfer	-	15			
					Bend	Bending die	15			
					Transport from station to storage	-	3.2	50.92	45.828	56.012
5	D		Cover C: sheath	Nylon	Transport to station from storage	-	2.72			
					Injection mould	Injection Mould	39.393			
					Transfer	-	15			
					Cut sprues and runners	-	32			
					Transport from station to storage	-	3.2	92.313	83.0817	101.5443
6	A		Support shaft	7mm Ø steel rod	Transport to station from storage	-	2.72			
					Thread ends	CNC Lathe	35			
					Transport from station to storage	-	3.2	42.75	38.475	47.025
6	B		Handle roller	Buy in						
6	C		Handle roller stopper, handleside	Nylon pellets	Transport to station from storage	-	2.72			
					Injection mould	Injection Mould	39.393			
					Transfer	-	15			
					Cut sprues and runners	-	32			
					Transport from station to storage	-	3.2	92.313	83.0817	101.5443
6	D		Handle lock	24mm x Ø 14mm steel rod	Transport to station from storage	-	2.72			
					Machining total set up/removal time	-	2.91			
					Machine smaller diameter	CNC Lathe	35			
					Transfer	-				
					Through Hole	CNC Mill	38			
					Transport from station to storage	-	3.2	81.83	73.647	90.013

Table A4: Component manufacturing processes, process timings and raw material for Parts 6E-6O. Continued from Table A2 & A3.

6	E		Handle roller stopper, gearside	Nylon	Transport to station from storage	-	2.72			
					Injection mould	Injection Mould	39.393			
					Transfer	-	15			
					Cut sprues and runners	-	32			
					Transport from station to storage	-	3.2	92.313	83.0817	101.5443
6	F		Spur Gear	40mm x Ø 14mm Steel rod	Transport to station from storage	-	2.72			
					Machining total set up/removal time	-	2.91			
					Cut teeth	CNC Mill	1.96			
					Transfer	-				
					Cut to desired thickness	CNC Lathe	5.32			
					Transport from station to storage	-	3.2	16.11	14.499	17.721
6	G		Gear bearing/lock		Transport to station from storage	-	2.72			
					Machining total set up/removal time	-	2.91			
					Internal milled	CNC Mill	25			
					Transfer	-				
					Cut to diameter	CNC Lathe	35			
					Transport from station to storage	-	3.2	68.83	61.947	75.713
6	H		Washer	Steel sheet	Transport to station from storage	-	2.72			
					Shear to shape	Shear die	15			
					Transport from station to storage	-	3.2	20.92	18.828	23.012
6	I		Adjustable roller stopper, gearside	Nylon	Transport to station from storage	-	2.72			
					Injection moulding	Injection mould	39.393			
					Transfer		15			
					Cut sprues and runners		32			
					Transport from station to storage	-	3.2	92.313	83.0817	101.5443
6	J		Adjustable roller stopper, handleside	Nylon	Transport to station from storage	-	2.72			
					Injection moulding	Injection mould	39.393			
					Transfer		15			
					Cut sprues and runners		32			
					Transport from station to storage	-	3.2	92.313	83.0817	101.5443
6	K		Adjustable Shaft	7mm Ø steel rod	Transport to station from storage	-	2.72			
					Machining total set up/removal time	-	2.91			
					Cut diameters and thread	CNC Lathe	76			
					Transfer	-				
					Mill flat sides on cylinder	CNC Mill	34			
					Transport from station to storage	-	3.2	118.83	106.947	130.713
6	L		Bracket	Steel sheet	Transport to station from storage	-	2.72			
					Shear to shape	Shear die	15			
					Transfer	-	15			
					Hole punch	Punching die	15			
					Transfer	-	15			
					Drawn into shape	Drawing die	15			
					Transport from station to storage	-	3.2	80.92	72.828	89.012
6	M		Spring for adjuster	Buy in						
6	N		Adjustable thickness handle inner	Steel sheet	Transport to station from storage	-	2.72			
					Shear to perimeter	Shear die	15			
					Transfer	-	15			
					Hole punch	Punching die	15			
					Transfer	-	15			
					Draw into shape	Drawing die	15			
					Transport from station to storage	-	3.2	80.92	72.828	89.012
6	O		Adjustable thickness handle outer	Steel sheet	Transport to station from storage	-	2.72			
					Shear to perimeter	Shear die	15			
					Transfer	-	15			
					Draw into shape	Drawing die	15			
					Transport from station to storage	-	3.2	50.92	45.828	56.012

Appendix B – Monthly Sales Estimates

One method used Amazon.com sales flow data from the U.S market, accessed through JungleScout [22], retrieving data for 3 pasta makers on the store, shown in Table B1. The mean of the monthly sales is calculated as 2260 sales /month. The second method took the approach of estimating the Total Available Market (TAM) of pasta makers. With the estimate for TAM at 1.22m sales per year, estimating the Serviceable Available Market (SAM) at 50% and assuming that *Acme* will be able to sell to 5% of SAM, a similar result of 2500 sales/month was calculated. This latter figure was used as the average monthly demand going forward.

Top-Down Method

Table B1: JungleScout data summary.

Product	Price	Rank (Kitchen & Dining)	Monthly sales
Nuvantee (#2 ABS)	$53.99	1,854	3660
Marcato Atlas (#3 ABS)	$84.95	2,606	2820
CHEFLY (case study)	$39.98	28,957	300

ABS = Amazon Best Seller ranking (pasta makers)

Bottom-Up Method

- 12m households in the US (US Census Bureau)
- 1/100 households will buy a pasta maker each year for the next 10 years

$$12m\ [households] * \frac{1}{100}\left[\frac{sales}{household\ year}\right] = 1.22m\ [\frac{sales}{year}]$$

- 50% of those purchases will fall into Served Available Market (SAM)
- Estimate it's possible to service 5% of that market ≈ 2500 $\left[\frac{sales}{month}\right]$

Seasonal Demand Modelling

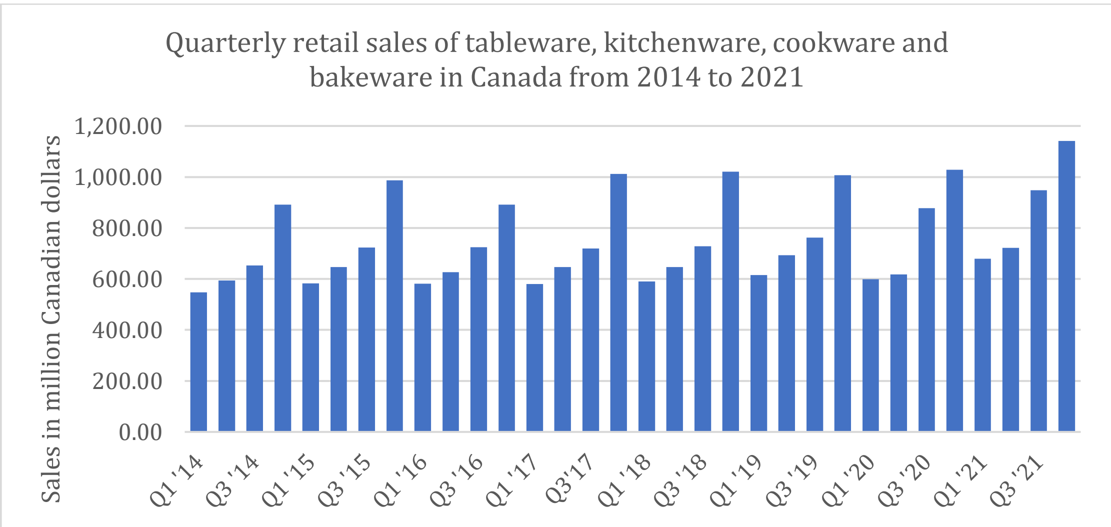


Figure B1: Quarterly retail sales of tableware, kitchenware, cookware and bakeware in Canada from 2014 to 2021 [23]

On average across all years 2014-2021, Q4 sales outperformed the mean of Q1-3 by 48.6%.

Therefore, in the estimate, Q4 sales ≈ 1.4x Q1 and Q2 and Q3 sales

Prime Days:

- July = 1.2x Jan
- Oct = 1.4x Jan

Average ≈ 2500 sales/month

Table B2: Monthly Demand Estimates

Month	Sales
Jan	2150
Feb	2200
Mar	2300
Apr	2200
May	2300
Jun	2350
Jul	2580
Aug	2300
Sep	2350
Oct	3010
Nov	3118
Dec	3548
Average	**2534**

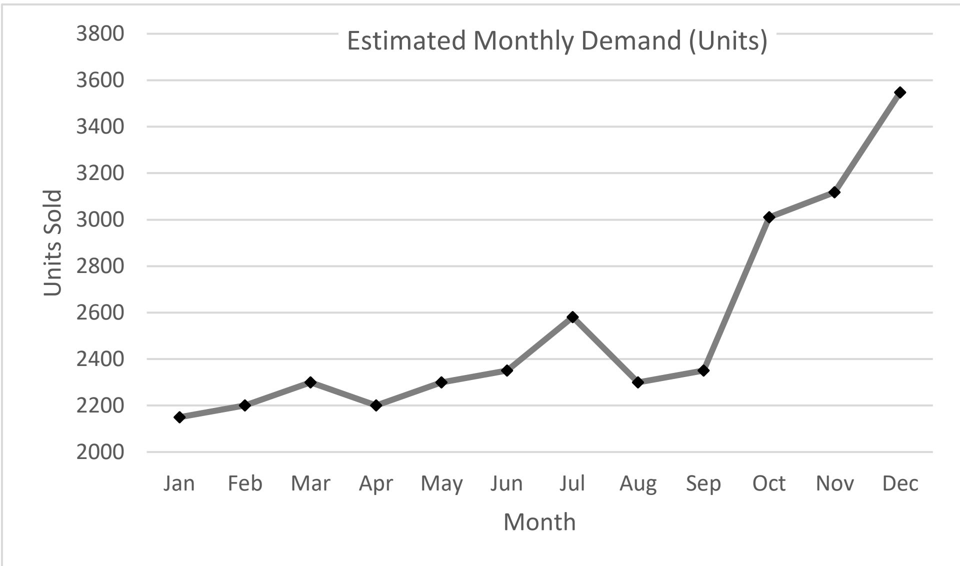


Figure B2: Plot of Monthly Demand Estimates

Appendix C – Pugh Matrix KPI Selection

Table C1: Push Matrix metric ranking for KPI selection.

	Measurability	Potential to improve				Score	Multiplier
		Flexibility	Quality	Reliability	Delivery		
Measurability	-	-1	-1	-1	-1	-4	1
Flexibility	1	-	1	1	1	4	5
Quality	1	-1	-	-1	-1	-2	2
Reliability	1	-1	1	-	-1	0	3
Delivery	1	-1	1	1	-	2	4

Table C2: Push Matrix KPI selection.

KPI	Measurability	Flexibility	Quality	Reliability	Delivery	Result
Throughput	Baseline					0
Lead time	0	1	0	0	2	13
Cycle time	0	0	0	0	1	4
Delivery reliability	0	-1	-1	1	1	0
Capital pay-back period	-2	-1	-1	-1	0	-12
WIP	2	0	0	0	1	6
System utilisation	0	1	1	0	0	7
Availability	-1	-1	0	-1	0	-9
Efficiency	-2	0	0	0	0	-2

Appendix D – Aspects influencing KPIs

Table D1: Summary of aspects of the production system and consideration for optimisation.

Area	Aspect	Aspect changes for optimisation	KPIs influenced	Considered
Manufacture	Capacity of operating machines	Increase	Lead time	N
	Machine operating time	Decrease	Lead time	Y
	Number of parts requiring a machine	Decrease	WIP	N
	Idle time	Decrease	System utilisation, Lead time, WIP	Y
	Number of machines	Increase	System utilisation, lead time, WIP	Y
	Waste parts per 1000 units	Decrease	System utilisation, WIP, Lead time	N
Transport & Buffers	Time spent in buffers per part	Decrease	Lead time, System utilisation, WIP	N
	Transport time between stations	Decrease	Lead time	N
	Number of parts in buffer	Decrease	WIP	N
	Buffer size	Decrease	WIP	N
Assembly	Total time for assembly	Decrease	Lead time	Y
	Time assembling as a factor of total time at station	Increase	System utilisation	N
	Batch Size	Decrease	Lead Time, WIP	Y
	Skills of workers	Increase	Lead time	Y
	Number of workers	Increase	Lead time	Y
	Number of failed assemblies per 100	Decrease	WIP, System Utilisation	Y
Design	Number of parts in design	Decrease	WIP	Y
	Number of parts in assembly	Decrease	WIP	Y
Global	Factory operating hours	Increase	Lead time	N

Appendix E - Scheduling Baseline

Table E1: Baseline Assumptions

Assumption	Description
1	Annual demand of 30,000
2	Components and assemblies are made ASAP with parallelisation
3	One operator per component manufacturing job
4	Two assembly workers
5	Productive rate best-case & worst-case scenarios are calculated using timing estimates ±10%
6	250 working days
7	The factory starts with 2500 of each component
8	Infinite stock
9	Multi-processed parts have total time combined and associated with dominant machine type
10	Buffers at each station, capable of holding 10 components
11	Transfer time between buffers taken as 15 seconds
12	All components are manually transferred between machines and stations
13	Sheet metal dies are compound
14	Injection moulding machine parts are bought in
15	Workers are full time and hired through the year
16	Daily demand with seasonal fluctuations Appendix
17	One operator per station
18	Stations of each type can be re-configured for multiple similar jobs
19	Multiple workers can work on the same job
20	Productive rate is taken as the middle of best & worse case scenarios (productive rate distribution is added in sensitivity analysis)
21	A component that is required twice in an assembly can be modelled as a single component that takes twice as long
22	First 5 days have no demand

Key
Linear programming model specific
Baseline model specific
General

Table E2: Summary of KPI data calculated from the baseline annual production run

Scenario	Average System Utilisation	Average WIP
Best Case	0.39	205,852
Worst Case	0.32	179,081

Best case and worst case are defined by the ranges provided in the component processing timings detailed in Appendix B Tables B2-B4.

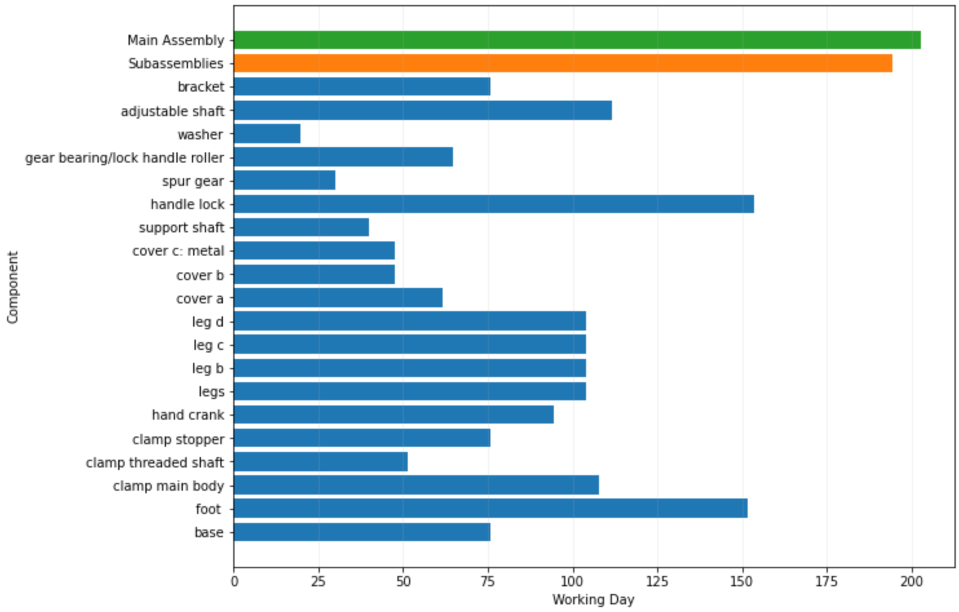


Figure E1: Baseline schedule – each component is produced by a single worker

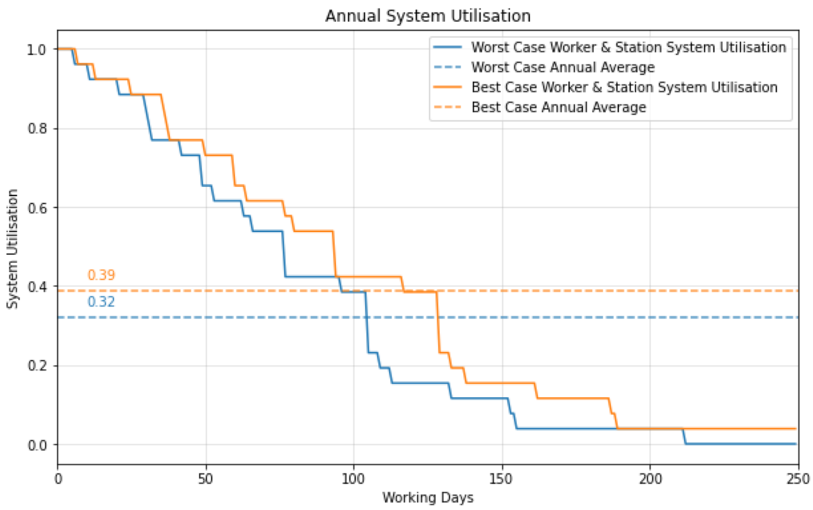


Figure E2: System Utilisation of baseline schedule

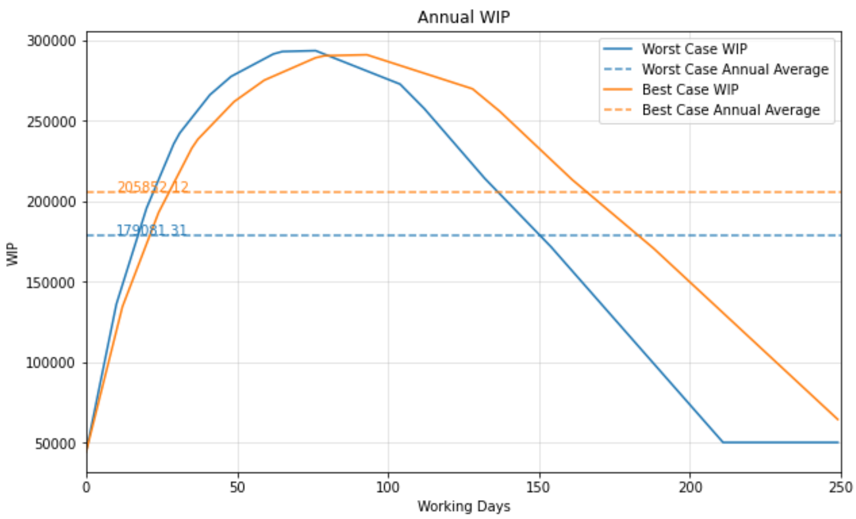


Figure E3: Work in Process of baseline schedule

Appendix F - Model Definition

Table F1: Model Definition

Symbol	Description
Decision variables	
$d_{j,o,t}$	Binary variable: 1 if the job *j* is being carried out by die machine operator *o* on day *t.* 0 otherwise.
$a_{j,o,t}$	Binary variable: 1 if the job *j* is being carried out by assembler *o* on day *t.* 0 otherwise.
$m_{j,o,t}$	Binary variable: 1 if the job *j* is being carried out by mill operator *o* on day *t.* 0 otherwise.
$l_{j,o,t}$	Binary variable: 1 if the job *j* is being carried out by lathe operator *o* on day *t.* 0 otherwise.
$W^s_{j,o,t}$	Generalised Decision Variable: 1 if the job *j* is being carried out by station *s* operator *o* on day *t.* 0 otherwise. Used for brevity in model description.
Constraints	
O	The set of operator types $\{O_d, O_a, O_m, O_l\}$
O^s	The set of operators that can operate stations of type *s,* {1, 2, …, N} where there are *N* operators of station type *s*
S	The set of station types $\{d, a, m, l\}$ corresponding to dies, assemblers, milling machines, and lathes.
Ω	The set of assembly jobs {SA1, SA2, SA3, SA4, SA5, MA}
ω	The set of components corresponding to assembly $\bar{\omega}$, $\bar{\omega} \in \Omega$
J	The set of jobs
J^s	The set of jobs that can be performed at station type *s*
$J_{\bar{\omega}}$	The job corresponding to production of assembly $\bar{\omega}$, $\bar{\omega} \in \Omega$
J_{MA}	The job corresponding to the production of the major assembly (MA) / final product
SA1	$\{J_{15}, J_{16}\}$
SA2	$\{J_{13}\}$
SA3	$\{J_2\}$
SA4	$\{J_3, J_4, J_5\}$
SA5	$\{J_6\}$
MA	$\{J_1, J_7, J_8, J_9, J_{10}, J_{11}, J_{12}, J_{14}, J_{17}, J_{18}, J_{19}, J_{20}, J_{22}, J_{23}, J_{24}\}$
Indices	
j, j'	Job index
o	Operator index
t	Time-step index (1 or 5 days)
s	Station type index
Model properties	
P_j	Daily productive rate of job *j*
$\tau_{j\,j'}$	Number of down-time steps associated with switching operator between jobs *j* and j'
φ_j	Duration of job *j*
t'	The time step associated with the beginning of the job j'
Ψ_t	Demand on day *t*

Appendix G - Problem Solutions

```
Gurobi Optimizer version 10.0.0 build v10.0.0rc2 (win64)
Copyright (c) 2022, Gurobi Optimization, LLC

Read LP format model from file C:\Users\felix\AppData\Local\Temp\aae8fa7626ca4d0e967aaafc68c82d9f-pulp.lp
Reading time = 0.08 seconds
OBJ: 1501 rows, 4201 columns, 137746 nonzeros

CPU model: AMD Ryzen 5 4500U with Radeon Graphics, instruction set [SSE2|AVX|AVX2]
Thread count: 6 physical cores, 6 logical processors, using up to 6 threads

Optimize a model with 1501 rows, 4201 columns and 137746 nonzeros
Model fingerprint: 0x1ec2782e
Variable types: 1 continuous, 4200 integer (4200 binary)
Coefficient statistics:
  Matrix range     [1e+00, 2e+04]
  Objective range  [1e+00, 4e+00]
  Bounds range     [1e+00, 1e+00]
  RHS range        [1e+00, 3e+04]
Presolve added 9 rows and 0 columns
Presolve removed 0 rows and 600 columns
Presolve time: 0.42s
Presolved: 1510 rows, 3601 columns, 82381 nonzeros
Variable types: 0 continuous, 3601 integer (3467 binary)

Root relaxation: objective -1.102603e+02, 1018 iterations, 0.02 seconds (0.03 work units)

    Nodes    |    Current Node    |     Objective Bounds      |     Work
 Expl Unexpl |  Obj  Depth IntInf | Incumbent    BestBd   Gap | It/Node Time

     0     0 -110.26027    0   65          - -110.26027      -     -    0s
     0     0 -110.26027    0   59          - -110.26027      -     -    0s
     0     0 -117.23113    0   76          - -117.23113      -     -    0s
H    0     0                    -121.0000000 -117.63800  2.78%     -    1s
     0     0 -117.63800    0   89 -121.00000 -117.63800  2.78%     -    1s
     0     0 -117.89263    0   70 -121.00000 -117.89263  2.57%     -    1s
     0     0 -119.67351    0   73 -121.00000 -119.67351  1.10%     -    1s
     0     0     cutoff    0      -121.00000 -121.00000  0.00%     -    1s

Cutting planes:
  Gomory: 24
  Cover: 23
  MIR: 58
  StrongCG: 23
  GUB cover: 1
  Zero half: 1
  RLT: 4

Explored 1 nodes (4019 simplex iterations) in 1.35 seconds (1.13 work units)
Thread count was 6 (of 6 available processors)

Solution count 1: -121
No other solutions better than -121
```

Figure G1: GUROBI solver example log file

Appendix H - Schedule Sensitivity Analysis

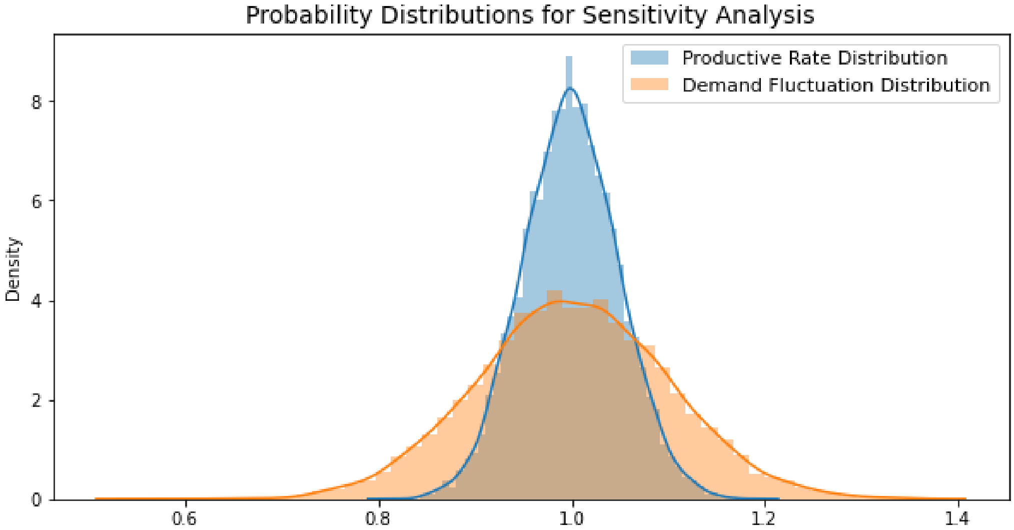


Figure H1: The probability distributions sampled from to introduce stochasticity to production rates and demand forecasts

The python library NumPy was used to sample from the normal distribution to scale both productive rate and demand fluctuation in sensitivity analysis of worker combinations. The same 5 sets of samples were drawn by setting the 'seed' argument of numpy.random.random

Table H1 – Summary of sampling distribution and seeds

Data	Distribution	seeds
Productive Rate	*~N(1, 0.05)*	[0, 2, 4, 6, 8]
Demand	*~N(1, 0.1)*	[1, 3, 5, 7, 9]

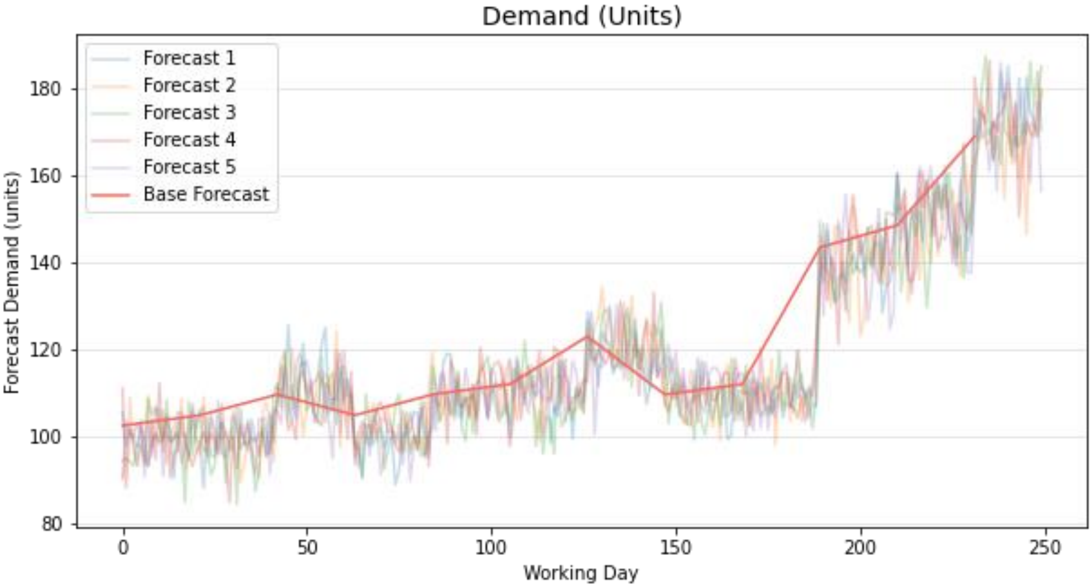


Figure H2: 5 forecasts used in the schedule optimisation sensitivity analysis with a scaled monthly demand forecast used as a basis. Each day's demand basis was taken to be 1/21st of its month's demand

Appendix I – Machining

Table I1: Machining Job ID, machine, and timings for a 2500 unit batch.

Part ID	Job ID	Machine	Machining Time (days +/- 10%)	Dependencies (Job ID)
2A	1	Mill	7.038	-
2A	2	Rod Bending	2.438	1
2B	3	Lathe	4.239	-
3A	4	Mill	2.003	-
3A	5	Lathe	3.805	4
3A	6	Rod Bending	2.438	5
6A	7	Lathe	3.110	-
6D	8	Lathe	3.284	-
6D	9	Mill	3.392	8
6F	10	Mill	0.264	-
6F	11	Lathe	0.621	10
6G	12	Mill	2.264	-
6G	13	Lathe	3.197	12
6K	14	Lathe	6.756	-
6K	15	Mill	3.045	14

Table I2: Total operational times for CNC machines.

CNC Machine	Total operation time [days]
Lathe	25.011
Mill	18.007
Rod Bending	4.875

Table I3: Job sequences for the baseline and improved versions of the machining cell.

Version	Machine	Job Sequence
Baseline	Rod Bender	2,6
	Mill	1,4,9,10,12,15
	Lathe	3,5,7,8,11,13,14
Improved Sequence	Rod Bender	2,6
	Mill	10,9,12,1,4,15
	Lathe	8,14,7,11,13,3,5
Additional Lathe	Rod Bender	2,6
	Mill	10,12,4,1,15,9
	Lathe 1	7,8,5,3
	Lathe 2	14,11,13

Figure I1: The scheduling section of the Excel Model for the machining cell.

Lathe				Mill				Rod Bending			
Sequence	Type	Dependents	Job Time	Sequence	Type	Dependents	Job Time	Sequence	Type	Dependents	Job Time
3	1	0	122072	1	1	0	202700	2	2	1	70200
5	2	4	109572	4	1	0	57700	6	2	5	70200
7	1	0	89572	9	2	8	97700				
8	1	0	94572	10	1	0	7600				
11	2	10	17872	12	1	0	65200				
13	2	12	92072	15	2	14	87700				
14	1	0	194572								

Lathe			Mill			Rod Bending	
SL	EL	Job time	SM	EM	Job time	SRB	ERB
0	122072	122072	0	202700	202700	202700	272900
260400	369972	109572	202700	260400	57700	369972	440172
369972	459544	89572	554116	651816	97700		
459544	554116	94572	651816	659416	7600		
659416	677288	17872	659416	724616	65200		
724616	816688	92072	1011260	1098960	87700		
816688	1011260	194572					
					End time:	1098960	

Appendix J – Assembly time estimation present-state vs lean-state

Table K1: Assembly time estimation by steps in assembly.

Stage	Processes	Actions	Time Estimation	Skill Level (1-3)	Lean design decisions	Lean Processes	Actions	Lean-Time Estimation
SA1	a. Press Nylon end caps x 2 for each roller b. Press Steel attachments into Nylon x 2	4 x no tolerance press 2x tolerance press	10s/ 15s/ **Total = 70s**	3	Press fit includes a physical end point requiring minimal worker precision	4 x no tolerance press		10s/ **Total = 40s**
MA1	a. Align Roller Assembly into Gear side Plate b. Add Gears c. Fit Washers	Insert roller assembly into inner side support x 2 Slide gear onto part x 2 Lock Washer x 2	4 s/ 4 s/ 10 S/ **Total = 36s**	3	External push on fastener would remove need for the link washer	a. Align Roller Assembly into Gear side Plate b. Add Gears c. Push on fastener	Insert roller assembly into inner side support x 2 Slide gear onto part x 2 Fastener x 2	4 s/ 4 s/ 2 S/ **Total = 20s**
MA2	a. Insert Bolt and center piece b. Align and insert bracket c. Screw on nuts	Align bracket x 1 Insert rod x 3 Screw nut x 2	5 s/ 5 s/ 8 s/ **Total = 36s**	2	n/a			
SA2	a. Adhesive b. Attach sheath c. Adhesive wait	X 2 X 2 Adhesive wait	10 s/ 5s/ 500 s **Total = 30s**	3	n/a			
MA3	a. Align and insert Sheet Metal covers	X 4	5s/ **Total = 20s**	1	n/a			
MA4	a. Align and insert side support b. Screw on nuts	X 1 (aligning 8 parts) X 2	10s 8s/ **Total = 26s**	2	n/a			
SA3	a. Align and insert pads	X 2	5s/ **Total = 10s**	3	Replace with a single base part	[redacted]		
MA5	a. Align Feet b. Align and insert Screws c. Screw on nuts	X 2 X 4 X 4	5s/ 3s/ 8s/ **Total = 54s**	1	Reworking to single base. Legs snap-fit in replacing M6 screws.	a. Align feet pads and manually press in b. Snap-fit legs	X 4	5s/ **Total = 20s**
MA6	a. Align and insert outer cover b. Align and insert screw c. Screw on nut	X2 X2 X2	5s/ 5s/ 8s/ **Total = 36s**	2	Replace M6 screws with snap fit outer casing	a. Align and snap fit outer cover	X2	5s/ **Total = 10s**
MA7	a. Align inner adjuster b. Align and insert spring c. Screw on nut d. Align and insert outer adjuster	X 1 X 1 X 1 X 1	4s 4s 8s/ 5s **Total = 21s**	2	n/a			
SA4	a. Adhesive plastic handle and threaded section b. Insert and screw in threaded rod c. Screw on flat plate d. Adhesive Cure	X 1 X 1 X 1 Adhesive wait	15s 8s/ 8s/ 500s **Total = 31s**	3	Clamp redesign to all metal.	a. Insert and screw in threaded rod b. Screw on flat plate	X 1 X 1	8s/ 8s/ **Total = 16s**
SA5	a. Insert handle grip onto rod	X 1	**Total = 5s**	1	n/a			

Appendix K – PERT Distribution calculations for assembly time estimation based on worker skill level.

Table L1: Distribution of assembly time by skill level

Skill level	Uncertainty in assembly time
1	-5% +5% - PERT dist.
2	-10% +15% - PERT dist.
3	-10% +30% - PERT dist.

The PERT distribution is a variation of the continuous beta distribution. It is useful when you know a most likely value and provide an upper and lower bound to the estimate. Upper and lower bounds in this analysis have been assumed based on the skill required to complete assembly stages considering tools required, machine skills, and number of parts. Three parameters govern the PERT distribution:

a = minimum value

b = mode

c = maximum value

It is defined the mean and standard deviation take the following values [24]:

$$\mu = \frac{a+4b+c}{6} \qquad \sigma = \frac{c-a}{6}$$

In Excel the PERT distribution can be calculated using BETA.DIST(x, α, β, FALSE, a, b) where

$$\alpha = \frac{4(b-a)}{c-a} + 1 \qquad \beta = \frac{4(c-b)}{c-a} + 1$$

An example probability density function (pdf) of MA1 with a skill level of 3 is shown in Figure L1 below. This pdf governs the random variable selection of assembly time for MA1.

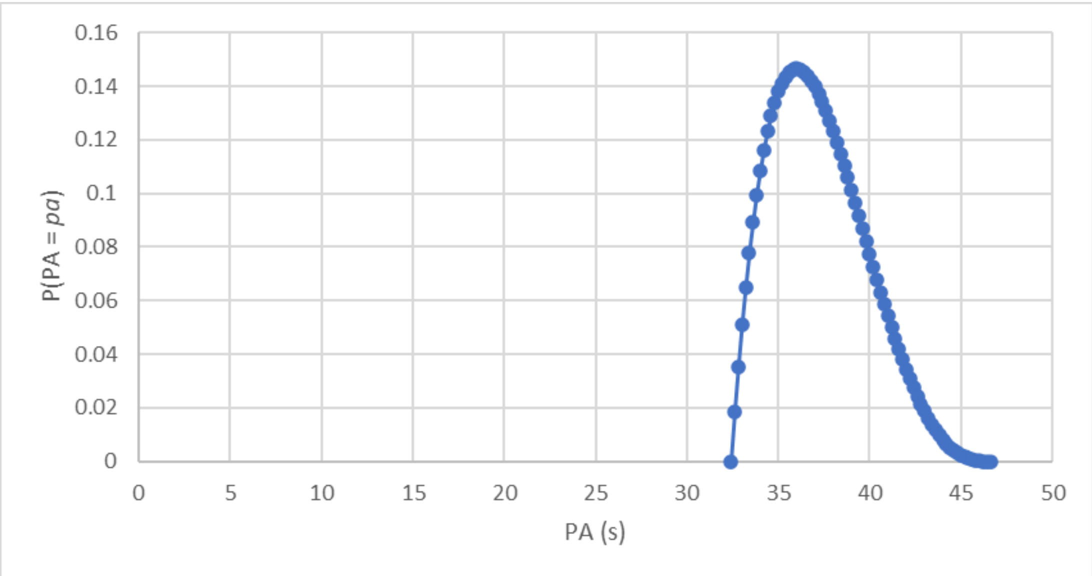


Figure L1: pdf of assembly time for MA1

Appendix L – Product reprocessing and probability of failure.

Table M1: Distribution of probability of failure by skill

Skill level	P(Fail) - Triangular(min,max,mode)
1	0.00475,0.00525,0.005 (+/- 5%)
2	0.009,0.0115,0.01 (-10% +15%)
3	0.0135,0.0195,0.015 (-10% +30%)

Table M2: Identified errors and assumed probability.

Assembly stage	Potential error	P_f (Fail)
MA1	a. Gears misaligned b. Rollers assembled in incorrect mirrored position	0.015 +0.01= 0.025
MA2	a. Missing bracket protecting gear mechanism b. Support shafts in incorrect mirrored position	0.015 +0.01 =0.025
MA3	-	-
MA4	a. Roller system not flush due to inadequate tightening b. Missing cover	0.015 +0.01 =0.025
MA5	a. Legs fixed in the wrong orientation b. Screws not tightx4	0.01 +0.005x4 =0.03
MA6	a. Screws not tightx2	0.005x2 = 0.01
MA7	a. Faulty spring	0.01
SA1	a. Missing roller bearing	0.015
SA2	a. Adhesive not provided time to dry	0.015
SA3	-	-
SA4	a. Adhesive not provided time to dry b. Clamp specific fault - flat plate not fixed	0.015 +0.01 = 0.025
SA5	-	-
MA1/2	$P_{f_{MA1}} + P_{f_{MA2}}$	0.05
MA3/4	$P_{f_{MA3}} + P_{f_{MA4}}$	0.025
MA5/6/7	$P_{f_{MA5}} + P_{f_{MA6}} + P_{f_{MA7}}$	0.05

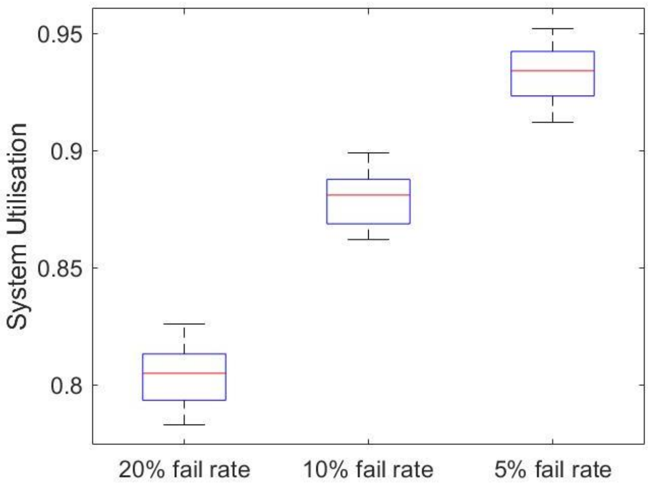


Figure M1: System Utilisation in the quality-at-source process design for different product failure rates at high demand.

Appendix M – Example Assembly WIP graphs

Baseline – Batch variation

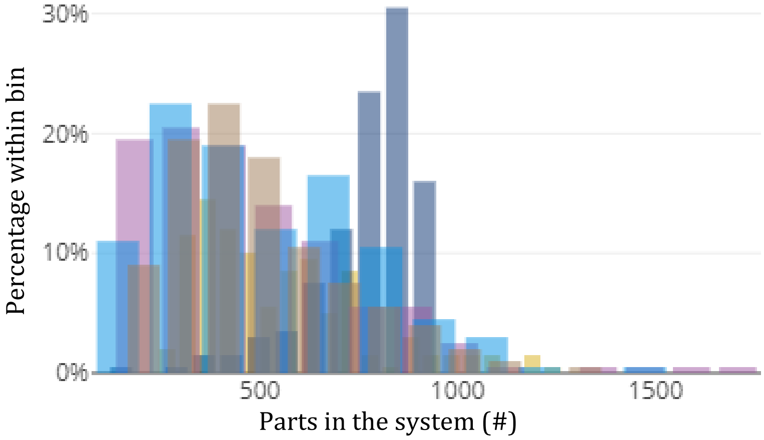


Figure N1: Batch variation histogram for the baseline system

Table N1: Batch variation with mean WIP

Batch Size	Mean WIP
1	770
2	505
3	475
4	505
5	550